REPORT RESUMES

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INTEGRATION OF STIMULUS CUES BY NORMAL AND MENTALLY RETARDED CHILDREN. FINAL REPORT.

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TWO EXPERIMENTS WERE CONDUCTED IN ORDER TO OBTAIN A MATHEMATICAL DESCRIPTION OF THE PERCEPTUAL PROCESS BY WHICH NORMAL AND MENTALLY RETARDED SUBJECTS SYNTHESIZE STIMULUS CUES IN PERCEPTUAL IDENTIFICATION. THE INITIAL STUDY EMPLOYED 50 COLLEGE STUDENTS, 34 GRADE SCHOOL STUDENTS, AND 24 MENTALLY RETARDED CHILDREN (AGES 9-16) AS SUBJECTS. THE SUBJECTS WERE REQUIRED TO MAKE A BINARY CLASSIFICATION OF 400 PICTURES IN WHICH THREE STIMULUS CUES WERE SHOWN THROUGH 20 VARIATIONS. THE VARIATIONS WERE RELATED TO THE CLASSIFICATIONS IN A PROBABILISTIC MANNER. IN THE SECOND STUDY, 128 HIGH SCHOOL, 89 GRADE SCHOOL, AND 110 MENTALLY RETARDED SUBJECTS WERE REQUIRED TO MAKE A SIMILAR CLASSIFICATION OF 400 PICTURES IN WHICH FOUR STIMULUS CUES WERE PRESENT. SUBJECTS WERE REQUIRED TO PLACE A WAGER ON WHETHER A PICTURE BELONGED TO ONE OR OTHER OF THE TWO CLASSIFICATIONS. SUBJECTS WERE ALLOWED TO VARY THE AMOUNT WAGERED. IT WAS ASSUMED THAT THE AMOUNT WAS A QUANTITATIVE INDEX OF THE SUBJECT'S DEGREE OF CERTAINTY OF THE CLASSIFICATION. IT WAS ESTABLISHED THAT AS MENTAL AGE INCREASES THERE IS A GREATER TENDENCY FOR HIGH AND LOW PROBABILITY EVENTS TO INFLUENCE THE EVOLUTION OF A PERCEPT. ALSO NOTED WAS A MORE PROMISCUOUS IRRADIATION OF THE EFFECT OF REINFORCEMENT (STIMULUS GENERALIZATION) FOR SUBJECTS OF LOW INTELLIGENCE. A MODEL WAS CONTRIVED IN DESCRIPTION OF THE DATA, AND SUGGESTIONS WERE FOR AN APPLICATION OF THE FINDINGS TO THE EDUCATION AND DIAGNOSIS OF THE MENTALLY RETARDED. REFERENCE LIST INCLUDES 21 ITEMS. (AUTHOR)

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U.S. DEPARTMENT OF
HEALTH, EDUCATION, AND WELFARE

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Bureau of Research

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TABLE OF CONTENTS

		Page
Abstract		iii
List of Figures		iv
Section I:	Introduction	1
Section II:	History	7
Section III:	Two Choice Response to the Three Stimulus Problem	13
Section IV:	Quantitative Responses to Stimulus Aggregates	45
Section V:	General Discussion and Summary	69
References		74

ABSTRACT

Two experiments were conducted in order to obtain a mathematical description of the perceptual process by which normal and mentally retarded subjects synthesize stimulus cues in perceptual identification.

The initial study employed college students, grade school students and mentally retarded children as subjects. The subjects were required to make a binary classification of four hundred pictures in which three stimulus cues were shown through twenty variations. The variations were related to the classifications in a probabilistic manner.

In the second study, high school, grade school and retarded subjects were required to make a similar classification of four hundred pictures in which four stimulus cues were present. Subjects were required to place a wager on whether a picture belonged to one or other of the two classifications. Subjects were allowed to vary the amount wagered. It was assumed that the amount was a quantitative index of the subject's degree of certainty of the classification.

It was established that as mental age increases there is a greater tendency for high and low probability events to influence the evolution of a percept. Also noted was a more promiscuous irradiation of the effect of reinforcement (stimulus generalizations) for subjects of low intelligence.

A model was contrived in description of the data, and suggestions were made for an application of the findings to the education and diagnosis of the mentally retarded.

LIST OF FIGURES

Figure	Title	Page
1	Distribution of cue variations for head position of the X and Y stimulus population	16
2	Distribution of cue variations for arm position of the X and the Y stimulus population	16
3	Distribution of cue variations for leg position of the X and the Y stimulus population	16
4	Mean percentage of reinforcement for the three groups as a function of trial block. Each block consists of 50 trials.	29
5	Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P1 Solution	30
6	Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P1 Solution	30
7	Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P1 Solution	30
8	Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P2 Solution	31
9	Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P2 Solution	31
10	Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P2 Solution	31
11	Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P3 Solution	32
12	Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P3 Solution	32
13	Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P3 Solution	32
14	Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P4 Solution	33
15	Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P4 Solution	33
16	Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P4 Solution	33

Figure Title Page

17 Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P5 Solution 34

18 Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P5 Solution 34

19 Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P5 Solution 34

20 Mean algebraic difference D between empirical data and predicted results based upon G3, P1 Solution 35

21 Mean algebraic difference D between empirical data and predicted results based upon G2, P1 Solution 35

22 Mean algebraic difference D between empirical data and predicted results based upon G1, P1 Solution 35

23 Mean algebraic difference D between empirical data and predicted results based upon G3, P2 Solution 36

24 Mean algebraic difference D between empirical data and predicted results based upon G2, P2 Solution 36

25 Mean algebraic difference D between empirical data and predicted results based upon G1, P2 Solution 36

26 Mean algebraic difference D between empirical data and predicted results based upon G3, P3 Solution 37

27 Mean algebraic difference D between empirical data and predicted results based upon G2, P3 Solution 37

28 Mean algebraic difference D between empirical data and predicted results based upon G1, P3 Solution 37

29 Mean algebraic difference D between empirical data and predicted results based upon G3, P4 Solution 38

30 Mean algebraic difference D between empirical data and predicted results based upon G2, P4 Solution 38

31 Mean algebraic difference D between empirical data and predicted results based upon G1, P4 Solution 38

32 Mean algebraic difference D between empirical data and predicted results based upon G3, P5 Solution 39

33 Mean algebraic difference D between empirical data and predicted results based upon G2, P5 Solution 39

Figure	Title	Page
34	Mean algebraic difference D between empirical data and predicted results based upon G1, P5 Solution	39
35	Correlation r between empirical data and predicted results based upon the G3, P1 Solution	40
36	Correlation r between empirical data and predicted results based upon the G2, P1 Solution	40
37	Correlation r between empirical data and predicted results based upon the G1, P1 Solution	40
38	Correlation r between empirical data and predicted results based upon the G3, P2 Solution	41
39	Correlation r between empirical data and predicted results based upon the G2, P2 Solution	41
40	Correlation r between empirical data and predicted results based upon the G1, P2 Solution	41
41	Correlation r between empirical data and predicted results based upon the G3, P3 Solution	42
42	Correlation r between empirical data and predicted results based upon the G2, P3 Solution	42
43	Correlation r between empirical data and predicted results based upon the G1, P3 Solution	42
44	Correlation r between empirical data and predicted results based upon the G3, P4 Solution	43
45	Correlation r between empirical data and predicted results based upon the G2, P4 Solution	43
46	Correlation r between empirical data and predicted results based upon the G1, P4 Solution	43
47	Correlation r between empirical data and predicted results based upon the G3, P5 Solution	44
48	Correlation r between empirical data and predicted results based upon the G2, P5 Solution	44
49	Correlation r between empirical data and predicted results based upon the G1, P5 Solution	44
50	Distribution of cue variations for head position of the X and the Y stimulus population	50

Figure Title Page

51 Distribution of cue variations for arm position of the X and the Y stimulus population 50

52 Distribution of cue variations for leg position of the X and the Y stimulus population 50

53 Distribution of cue variations for bar position of the X and the Y stimulus population 50

54 Mean percentage of reinforcement for the three groups as a function of trial block. Each block consists of 50 trials. 52

55 Mean absolute error obtained in predicting the empirical results from the G3, P1 Solution 56

56 Mean absolute error obtained in predicting the empirical results from the G2, P1 Solution 56

57 Mean absolute error obtained in predicting the empirical results from the G1, P1 Solution 56

58 Mean absolute error obtained in predicting the empirical results from the G3, P2 Solution 57

59 Mean absolute error obtained in predicting the empirical results from the G2, P2 Solution 57

60 Mean absolute error obtained in predicting the empirical results from the G1, P2 Solution 57

61 Mean absolute error obtained in predicting the empirical results from the G3, P3 Solution 58

62 Mean absolute error obtained in predicting the empirical results from the G2, P3 Solution 58

63 Mean absolute error obtained in predicting the empirical results from the G1, P3 Solution 58

64 Mean absolute error obtained in predicting the empirical results from the G3, P4 Solution 59

65 Mean absolute error obtained in predicting the empirical results from the G2, P4 Solution 59

66 Mean absolute error obtained in predicting the empirical results from the G1, P4 Solution 59

67 Mean absolute error obtained in predicting the empirical results from the G3, P5 Solution 60

Figure	Title	Page
68	Mean absolute error obtained in predicting the empirical results from the G2, P5 Solution	60
69	Mean absolute error obtained in predicting the empirical results from the G1, P5 Solution	60
70	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) High School Group G1 formula	61
71	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Grade School Group G1 formula	61
72	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Retarded Group G1 formula	61
73	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) High School Group G2 formula	62
74	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Grade School Group G2 formula	62
75	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Retarded Group G2 formula	62
76	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) High School Group G3 formula	63
77	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Grade School Group G3 formula	63
78	Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5) Retarded Group G3 formula	63
79	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) High School Group P1 formula	64
80	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Grade School Group P1 formula	64

Figure	Title	Page
81	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Retarded Group P1 formula	64
82	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) High School Group P2 formula	65
83	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Grade School Group P2 formula	65
84	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Retarded Group P2 formula	65
85	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) High School Group P3 formula	66
86	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Grade School Group P3 formula	66
87	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Retarded Group P3 formula	66
88	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) High School Group P4 formula	67
89	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Grade School Group P4 formula	67
90	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Retarded Group P4 formula	67
91	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) High School Group P5 formula	68
92	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Grade School Group P5 formula	68
93	Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3) Retarded Group P5 formula	68

SECTION I

INTRODUCTION

If mental retardates were of a species entirely separate from the normal, the analysis of their abilities would probably proceed in a more objective and orderly fashion. As it is, we are often satisfied to describe their behavior as defective, and certainly this is true from a social and pedagogical point of view. The idea of mental deficiency has burdensome teleological implications, however, when research and analysis are undertaken. The pathological is, after all, as natural as any other state of being, having its own rules and causative regulations. That these rules for organization tend to produce an organism that cannot compete in our society based upon our society's criteria of success, predisposes the researcher to making value rather than descriptive judgments. Instead of asking "what is the mental retardate like?", he asks "why is the mental retardate like that?"

Although there is no scientific impropriety in the second question it seems evident that the first question must be answered before the second can be properly stated. Thus we must obtain as broad and as concise a description of the mental defective as we can before asking why this description differs from our description of the normal. This is not to say that research at this time should not undertake a comparison of the defective with the normal. Descriptions are meaningful only in relation to other descriptions.

To attempt a description of mental retardation is to make the assumption that the mental retardates have much in common with one another. Just as we try to describe normal behavior based upon collective evidence, we also speak of mental retardation as a condition affecting many individuals. It is well to acknowledge that this assumption may not be altogether justified.

It may be that the things that the mentally retarded have in common with one another are not what they can do but what they can't do. If this is true, we have fallen into a grevious taxonomic error. This is somewhat like collecting men and fish into the same species because the inability to fly is common to both.

Classification using mental tests is largely made up of this type of negative reasoning. The individual making an IQ score of 60 is put into the category of the mentally defective because he can't answer the questions normals can answer. Another individual is similarly classified for the same reason. It may be, however, that the inabilities proceed out of totally dissimilar causes for the two people.

Mental retardation will finally be understood only through a program of classifying individuals on the basis of what they can do and how they do it, rather than upon their common disabilities. It is rather amazing, after all of the work and research effort that has been made on the mental retardates, how little we know about what they can do. We only know what they can't do. The consequence of this is that we do not know if we are working with one population or many populations. Etiological classifications may have their uses, but they contribute nothing to our understanding of what is occurring in the individual or how he is functioning. It seems evident that a great deal of systematic research will need to be done on mental retardation before we begin to classify. Even more will be required before we can begin to talk of probable causes.

The present research relates to many of the traditional areas of psychology. It can be regarded either as a study of learning or of perception. In a more restricted sense it can be thought of as information processing. It also has much in common with the stochastic learning models of recent development.

None of these appellations is especially descriptive. The basic question that was entertained in this work concerned how normal and retarded subjects refer to several stimulus cues simultaneously in the production of a decision. The terms "stimulus integration" and "stimulus synthesis" are to be used with care since they imply a perceptual or judgmental interaction of stimulus elements which may, in fact, not occur in all individuals. In making a series of judgments some persons may always rely on a single cue. Still others may decide which among the several cues available is most valid for that occasion and base the decision on the single element. On the next trial they might choose a different cue to which they respond. These processes would not fall into the definition of synthesis or integration since no real interaction of elements is involved.

The real life analogy to this experimental paradigm is easy to find. Indeed it can be said that almost all of human behavior relates to the area of multi-stimulus judgments. As an example, it can be said that the universe consists of two classes of things; cats and non-cats. For the greater part these two classes are quite distinguishable, but there are members of the non-cat class that one might erroneously assign to the population of cats. A small dog on a dark night might produce such an example. An infant lion might be another. How then does a child begin to distinguish between the two classes? Size is not a completely reliable index. Neither is color, nor the shape of the ears, nor the slant of the eyes. For any single classification that can be ascribed to cats there can be found a member of the non-cat population that possesses it. As an added difficulty it should also be said that cats are not precisely alike in terms of any feature that could be named in description of "catness." Yet the child learns to perceive certain things as cats quickly and without conscious effort.

It seems evident that perception is based upon the fusion of a number of stimulus elements, each of which can vary within measurable limitations. This statement, however, is to pose the question rather than to answer it since the problem remains as to how the stimulus elements are integrated. The task is to describe how the percept is generated. Such a description could be neurophysiological, chemical, anatomical, or one of many other possibilities. It is convenient at this stage, however, to describe the behavior in terms of the sequence of sensory events that take place. It is also useful to measure these events. For many persons a mathematical description or model is unsatisfactory since it does not necessarily tell one anything about the process. It is not necessarily true, for example, that a model of even high predictive power will increase our knowledge about the process it predicts. The relationship between the model and the process can be entirely fortuitous. This tends to be unlikely, however, especially for models having general application. Generally speaking, the terms or variables in the model are found to be to some extent isomorphic with the neurological or physiological factors that enter into the phenomenon.

Generally there are two approaches, one inductive and the other deductive, that can be taken in the development of a model. The deductive method would be to obtain the empirical data and write a mathematical description of it. It then remains to be deduced if the terms of the equation bear any apparent relationship to the anatomical and environmental factors that may enter into the event. The inductive approach goes in the opposite direction. Here one begins with certain ideas about how the process is generated, writes a mathematical description of the operation, and finally tries to see if the data fit the prediction of the model. As a practical matter the theorist ordinarily uses both the inductive and the deductive approaches availing himself of the restraints imposed by both his theory and his data. By means of a series of approximations he then seeks an adequate correlation between the two.

Returning to the notion of perceiving the world as consisting of cats and non-cats, a physical analogy to the process is the action of a seesaw. If the instrument is perfectly balanced and if undisturbed, it will remain in whatever position it is left. One side can be made to go up or down depending upon the distribution of weight on its surface. Thus if two weights, one weighing 5 pounds and another weighing 3 pounds are on one side at 2 and 5 feet from the fulcrum, respectively, they will be elevated by a 4 pound weight on the other side that is 7 feet from the fulcrum.

Something very like this goes on in perception. Some cues lend their weight to a non-cat judgment, others to a cat judgment. The final percept depends upon the total distribution of forces. One might hypothesize that the force is proportional to the frequency that a stimulus variation has been identified with one side or another. The distance would correspond to the just noticeable scale of stimulus differences. With a few added touches like a rolling fulcrum and a dihedral inclination of the board (so that the weights would tend to shift inward toward the center with time) a very respectable predictor model could be generated. The experimenter actually went through this exercise on some data and obtained a correlation of .56 between predicted and actual outcome. This is not high enough to be taken seriously as a model, but it does establish a certain analogy with the psychological event. It is quite likely that when all of the variables that are relevant to the problem of stimulus integration are known, that a seesaw could be built which would make an extremely close prediction of the perceptual event.

The research and analysis reported here is admittedly theoretical. It is not immediately certain how the results, whatever interpretation may be put upon them, will lend themselves to the training or the education of the mentally retarded. There is no reason, however, to be unnecessarily apologetic for this, since application often eventuates from research where utility is not an obvious factor. Nevertheless, it is incumbent upon the experimenter to structure his work within the context of some pragmatic definition of value. Otherwise, research would be completely adrift without chart or compass to guide it.

In the present instance it is felt that the area of investigation is basic to a description or an understanding of mental processes whether defective or normal; and that if the results do not suggest an immediate way of compensating for the deficiencies of the retarded, they will form a portion of the substructure upon which more critical and definitive experiments can rest.

SECTION II

HISTORY

Stimulus integration is a contemporary term for a problem that anti-dates pre-scientific psychology by many years.

Historically, the theories of how organisms utilize sensory information have taken two broad paths. The first was concerned with the study of the elements of sensory experience and how they combine via associational processes to build ideas, percepts and images. The second viewed the organism as endowed with certain native perceptual integrating processes. It was concerned not with the elements that make up a percept, but with the wholes of phenomenal experience.

The antecedents of modern day association theory started in two countries. In England, British empiricism, beginning with Hobbes, Locke, Berkeley and others and ending in the associationism of James and J. S. Mill, made a great impact on western thinking (Boring, 1957). These English scholars emphasized the building of percepts from sensory inputs. They rejected the notion of innate ideas, animal spirits, and some of the mystical explanations of perception that were current in that day. In Germany a great deal of study was devoted to the sense organs. The emphasis of both these groups was on the elements assumed to make up the active mind. The British were more concerned with philosophy or theory, while German scholars emphasized stimulus attributes and the properties of nerve fibers. These efforts converged in the work of Wilhelm Wundt.

There existed in Germany at about the same time another school of thought which was working on quite different assumptions. What we now might call the holistic approach had its genesis in the works of men such as Kant, Hering, Stumpf and Müller, to name only a few. These men viewed the organism as having certain "givens." For example, the ability to perceive depth was assumed to be a faculty an organism had at birth. For these scholars, sensory information served only to activate the native unifying principles of the brain. These ideas were carried on in Gestalt psychology.

Gestalt psychology has not changed its position very much in the last fifty years. The rise of Gestaltism is partially explainable as a reaction to the atomistic associationism of Wundt and his students. It is the Gestaltists' argument that parts or elements of perception are only obtainable after the whole has been perceived. To study elements, then, is to study artifacts of the basic process. Gestalt psychology can handle a wide range of perceptual phenomena, but it leaves a broad area of behavior unaccounted for, particularly in the area of learning.

Accepting the Gestalt doctrine nearly precludes the necessity for experimentation. By definition, any type of analysis involves breaking up the wholes into artificial parts. The burden of experimentation has been carried on in the tradition of associationism. It is here that the methodological tools are available. Much of the work in this area has been confined to the studies of one stimulus parameter at a time. In this way it has been possible to determine the kinds of physical energies which the organism can detect and the limits of this detection ability.

Although a cleavage between the divergent approaches of the associationists and Gestaltists to the problem of stimulus synthesis and the use of sensory information still exists, there is some convergence of the different approaches. Notable among the attempts at convergence is the work of Donald Hebb (1949). Hebb has attempted to integrate contemporary perception and learning theory in a physiological theory. He argues that percepts are the product of learning. The only native ability an organism has at birth is the ability to distinguish figure from ground. He has accounted for the integration of stimuli by postulating reverberating circuits in the brain. Certain patterns of stimulation are described as giving rise to the firing of specified circuits of neurons. The percept is dependent upon the particular circuits aroused to action.

A somewhat broader approach has been utilized by some individuals in attempts to find the various stimulus parameters which will account for the variance of behavior (see: Arnoult, 1960; Attneave, 1957; Brunswik, 1940; Gibson, 1957). These studies are mostly concerned with defining the nature of the stimulus and the extent to which it can account for the behavior under study. The work of Egon Brunswik is most relevant to the present approach. Together with Tolman (Tolman and Brunswik, 1935), Brunswik presented an article on the causal texture of the environment. It was their contention that percepts were never absolute, only probable. Brunswik (1943, 1944, 1956) presented this thesis under the name of "probabilistic functionalism".

The organism is described by Brunswik as perceiving numerous cues from its environment. These acquire probability values with respect to their ability to arouse the "correct" percept. A correct percept is defined as one which enables the organism to function more adequately in its environment. This is, of course, a learning process. It is by responding to the percept aroused by assessing cues in a given manner that the organism obtains feedback about the appropriateness of its response. If the response is appropriate for the environmental adjustment needed, the probability values assigned the cues will remain about the same. However, if the response does not enhance adjustment, another weighting of the cues is likely. Brunswik's approach is molar in that he has attempted to explain how all sensory input can be combined to give rise to one percept. Yet, his approach is molecular from the standpoint that he views perception as the product of the multitude of information the organism receives.

The intriguing aspect of Brunswik's formulations lies in the assumed probabilistic nature of the environmental cues. The model not only poses the research problem of discovering which cues are most highly correlated with a percept (Brunswik, 1940), but it lends itself to the contemporary interest in probability learning. Stochastic models of learning have in recent years been given a great deal of attention (see: Bush and Mosteller, 1955; Estes and Burke, 1953). These models have met with varying degrees of success in predicting the form of a learning curve for a given stimulus situation. The behavior of animals and humans in many types of probability tasks has been studied extensively (see Hilgard, 1956, Chap. 11). Research surrounding these models has not, however, attempted to assess learning when multiple cues are presented.

Seldom, if ever, can behavior be accounted for by the study of one stimulus parameter. There are numerous potential stimuli acting on the organism at any given moment. These include all the proprioceptive stimuli acting from within the organism and all the extroceptive stimuli originating in the environment and conducted to the organism via the sensory processes. Proprioceptive stimuli include the biochemical imbalances and the homeostatic mechanisms, kinesthetic stimuli, and vestibular stimuli, while potential extroceptive stimuli consist of any energy change in the environment the sense organs are capable of relaying to the central nervous system. Taken together, the sources of stimulation are numerous. Assuming that a large number of potential stimuli are filtered out before they arrive at the point where they are instrumental in determining a response, there must still be substantial amounts of information to assess and synthesize before a response is made. The general purpose of the experiments presented in this report is to examine the process of stimulus synthesis. The term stimulus synthesis is used to describe the operations which occur when an organism combines and integrates the information (cues) it receives to effect a response. Quite obviously, the information used to arrive at a response must be evaluated. Some cues would be weighted rather strongly, others weakly, and some at values in between.

Elam (1962) reported several experiments in which attempts were made to describe the process human subjects used to synthesize stimulus cues in a learning task. Subjects viewed a series of slides having from one to four stimulus cues. Each of the cues had 20 or 21 variations and each variation had a predetermined probability of being reinforced for two categories of response, e.g., subjects could respond "left" or "right," "X" or "Y," "up" or "down," etc. Four hundred twenty such slides were used for each treatment group. Subjects viewed the slides, indicated their answers, and then were told which answer was "correct". Elam's experiments investigated three hypotheses of stimulus synthesis.

These he called the Linear, the Multiplicative, and the Log hypotheses. These were, more accurately, curve correlation procedures designed to describe the relationship between the separate cues contained in a stimulus presentation. The Linear method was based upon the assumption that the strength of the individual cues were in a simple additive relationship with one another. The Multiplicative hypothesis assumed that the stimulus configuration was perceived as a product of the strength of the separate cues. This procedure tended to give greater emphasis to high and low probability events. The Log hypothesis assumed that the medium probability events exerted the greatest relative influence on the percept.

These analyses indicated that the Linear and Multiplicative descriptions were more accurate than the Log hypothesis. The research is subject to criticism, however, because it did not take the sequence of stimulus presentations into consideration. It assumed, without justification, that the subject from the start of testing was responding to the probability levels of the total stimulus population that was finally presented. It is obvious that a subject could not know the cue parameters of this population until all the stimuli had been seen. This, of course, was only the case after the testing procedure was complete.

In a later study Elam (1964) rectified this fault by evaluating each trial on the basis of only the stimuli that had been exposed. In addition, consideration was given to the non-linearities of stimulus generalization. This produced a much more accurate prediction of performance. This study was also somewhat unsatisfactory. Although the models were generally accurate for the subject populations involved, the analyses did not show the continuity between the populations. What is needed is not a separate model for each level of intelligence, but rather a single model which can be adjusted to be descriptive of all levels.

The present study attempts to correct the faults of the earlier research. In addition, it explores procedures involving quantitative responses that had not been previously used. It was felt that quantitative responses should be investigated since they were likely to be more sensitive than two category responses. Quantitative responses were also introduced in a check on the generality of the model.

SECTION III

TWO CHOICE RESPONSE TO THE THREE STIMULUS PROBLEM

This, the first of the two major studies of this report, was designed to obtain data on the probability that a subject will make one of two possible responses based upon the information contained in three simultaneously presented stimulus cues. Although the concept is based upon the individual probability of response, these data are actually obtained from the variance in the group responses. Thus the assumption is that if it were possible to run the same individual through the test sequence many times without his being influenced from his previous experiences, he would produce a sample of responses which would not differ significantly from the sample obtained from the group. This idea is common to most experiments, but in this study it has a special significance because the individual probability is carried as an intervening variable in the analytical effort.

The philosophical difficulties of this assumption are recognized. It is as though the individual contained a number of conflicting tendencies within himself, any one of which could determine the characteristics of the perceptual event, and any one of which could occur on some random basis. There is no certitude, either on anatomical or physiological grounds for these assumptions. It is assumed because it is the way individuals usually behave.

METHOD

Subjects

These were obtained from three sources; college students, grade school students and the mentally retarded. The purpose here was to obtain a wide range, both in maturity and in intellect. It was thought that since the groups would yield strong differences in ability that the data would serve as strong anchors for the development of the model. This model later could be applied to groups having more similarity to one another.

There were 50 individuals in the college group. Sex differences were balanced. Academic level and major were random variables. All were volunteers.

The grade school student (N = 34) ranged between 7 and 11 years of age. They were also volunteers and enrolled in various schools in the metropolitan area. They are to be regarded as a fairly random sample, intellectually and socio-economically, of the grade school population.

The mental retardates (N = 24) were obtained from the State Institute at Denton. Their ages range from 9 to 16. All were given a Group IV classification based upon the rationale of Sloan & Birch (1955). The mean IQ based upon the records of the institution was 63. IQ range was 50 to 70.

Stimuli

This consisted of four hundred 35 mm slides. Each showed the picture of a girl in leotards and tights. There were three basic ways in which the pictures differed from one another. These were in the position of the girl's arms, the legs and the head. Each of these three cues had 20 variations. The head varied in 20 prescribed positions; Position No. 1 being fully turned to the right, and Position No. 20 turned fully to the left. Similarly the arms varied from being extended vertically over the girl's head downward through 20 positions until at the opposite extreme they rested down at her side. The legs also varied through 20 positions from being with the heels together in Position No. 1 to a position with the feet far apart in Position No. 20.

One half of the pictures were classified in the program as Xs. This is to say that when they were presented, the subject was reinforced for moving a toggle switch in a direction marked X. The remaining 200 slides were Ys since the subjects were told that their response was correct if they moved the switch to the Y direction when these were presented.

The position of the head, arms and legs had a probability relationship to the X and the Y classifications. This relationship is shown in Figures 1, 2 and 3 for the head, arm and leg positions respectively.

In the 400 pictures, each of the 20 positions of each variable occurred exactly 20 times. Except as the positions of arms, legs and head were related to the X and Y dichotomy, there was only a random association between the positions of the head and the legs. In other words, the correlation between the variable was limited to the requirement that they each bear the relationship to X and Y that is shown in these figures. The remaining variance was entirely random.

It had been originally intended to include auditory stimuli on magnetic tape (20 variations in each of pitch, loudness and phase) but this was found to be utterly impractical for all subjects. Some pilot studies were run using the auditory stimuli, but discrimination was found to be of such a low quality as to preclude the use of these variables in the type of experimental work performed here.

Procedure

The subjects were tested individually. Each sat before a special test apparatus having a translucent screen, an X-Y toggle switch, a trial completion switch and two indicator lights, one reading "right" and the other "wrong." On a given trial the designated picture was projected on the screen. The subject decided whether it was an X or a Y picture and moved the switch in the desired direction. He then pressed the completion switch which caused either the "right"

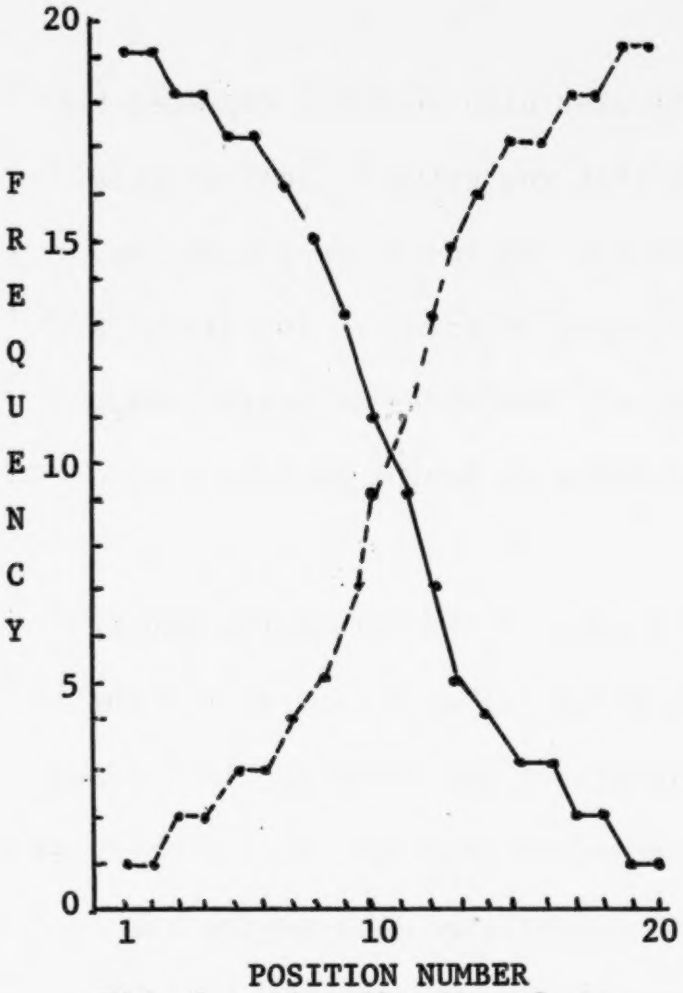

Fig. 1. Distribution of cue variations for head position of the X and the Y stimulus population.

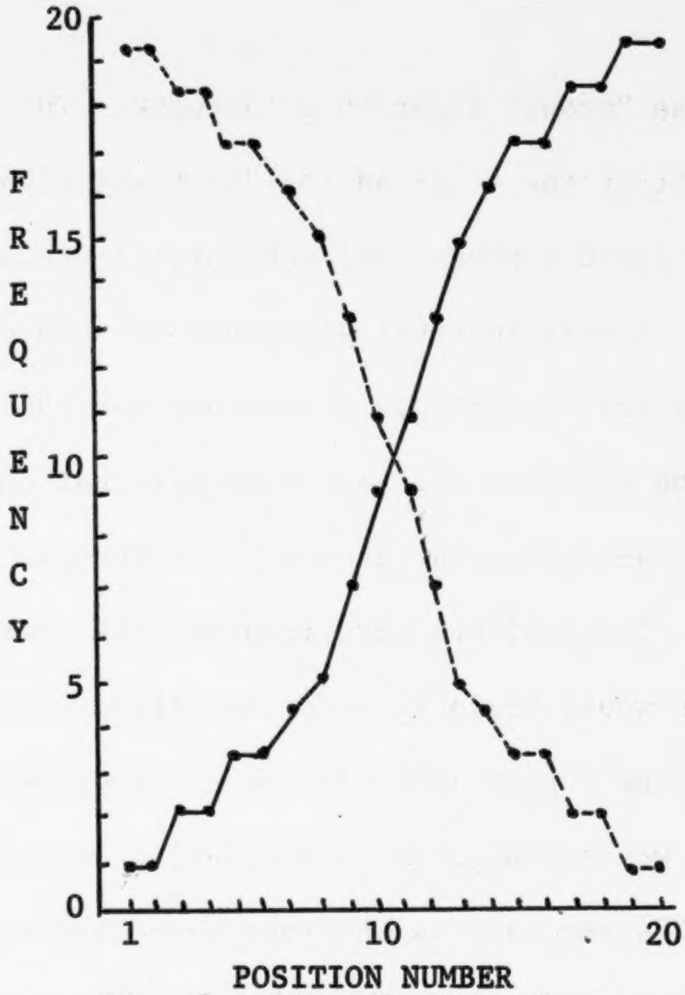

Fig. 2. Distribution of cue variations for arm position of the X and the Y stimulus population.

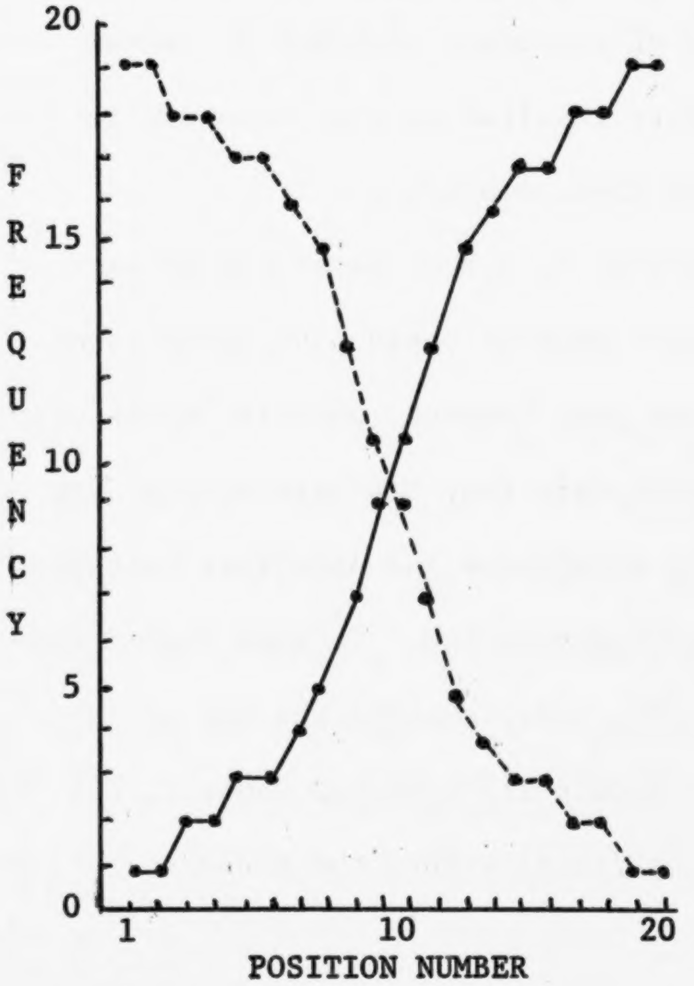

Fig. 3. Distribution of cue variations for leg position of the X and the Y stimulus population.

---- X Distribution

____ Y Distribution

or the "wrong" light to illuminate. The experimenter also verbally repeated the result of the trial saying "that was right" or "that was wrong." The subjects were given a penny for each correct response but nothing for a wrong response.

A rest interval was given between each block of 50 trials. Two blocks of fifty trials were given each day for the four days. The order of presentation of the pictures was random except that only a maximum of four X or four Y pictures were allowed to occur in sequence.

The subjects were treated alike except for some of the retardates who at times would begin to make repetitious responses by always selecting either the X or the Y position. In these few cases the experiment was arrested and explanation was again given to the subject concerning the fact that half of the pictures were Xs and half Ys and that much more would be accomplished by studying the picture carefully in order to determine whether an X or a Y response should be made.

This always served to break up this type of response, although it cannot always be said that the modification in procedure resulted in a substantial improvement in the frequency of reinforcement for these subjects.

In recent years a number of stochastic models have been developed as analogues to the human learning-perceptual process. Some of these have shown themselves to be good predictors of behavior. These are, however, usually "miniature systems" which have been constructed to deal with data that has been obtained in a particular manner and it is often found to be cumbersome and sometimes impossible to transpose them into a different experimental paradigm. To some degree this lack of generality reflects upon the models. If a model employs the use of intervening variables it can be a good predictor within its selected context, but at the same time it can be either trivial or artificial within the broader aspects of behavior. It is trivial if it makes a correct assessment of the influence of the variables that affect the phenomena, but in a manner so superficial as not to suggest how the model can be extended for the treatment of other situations. It is artificial if it has hit upon a fortuitous association that could only apply to the selected situation. In their final consequence, trivial models have a definite usefulness to the progress of understanding. Artificial models probably have a corrosive influence on the development of theory since they serve as unreliable guide posts to further exploration. The difficulty, of course, is in telling one from the other.

While the present analytical effort is somewhat different from that of others, it is not actually innovative since it employs concepts that have been in circulation for some time. It assumes, for example, that if a response is made in the presence of a stimulus and if the response is followed by reinforcement (knowledge that the response is correct), some incremental tendency is generated for that stimulus to elicite that response. Knowledge of results that the response is inappropriate would decrease its likelihood of occurrence, not by decreasing the strength of the association, but by increasing the strength of a competing response. This is very close to Hull's (1943) notion of habit strength.

The approach is associatistic rather than holistic. It assumes that the organism responds to the stimulus as a whole but not in a configurational manner. In other words, if a series of stimuli are to be dichotomized and if they contain multi-dimensional differences such as size, color, shape, texture, etc., it is assumed that each of these parameters exerts an independent and weighted influence on the final judgment. In effect, if not in exact concept, this approach corresponds to what has been called the Continuity Hypothesis of Lashley (1938).

The use of the idea of stimulus generalization is also in the tradition of Pavlovianism and neo-behaviorism. The use of "residual enertia" has some similarity to Helsen's Theory of Adaptation Level. The stochastic aspects of the model show many contemporary influences.

This study was conducted not so much to observe the behavior of the subjects as to predict the behavior observed. It is, however, of some interest to show at this point the relative scores of the three groups in obtaining reinforcement. These scores are shown in Figure 4. The performance levels are about as might be expected, considering the probability relationship of the stimulus cues to the X-Y classifications. The curves all begin somewhat above chance and make a significant ascension as the test proceeds. The differences between groups, based upon the means for the entire test, were all beyond the 99 per cent level of confidence as measured by an analysis of variance and by making individual comparisons using the T test.

It would be in error to regard these curves as being absolutely associated with good performance. In this study there is no absolute criteria for determining what perfect performance should be. Taking the usual notions of probability theories, one could evaluate each choice of the subject based upon the ratio $F_{X_A} \; F_{X_H} \; F_{X_L} \; / \; F_{Y_A} \; F_{Y_H} \; F_{Y_L}$ where F_{X_A} is the frequency that the particular variation for the arms had occurred on pictures labeled X prior to the trial being evaluated, and F_{Y_A} represents the number of times it had occurred on pictures labeled Y, etc. If the value of the ratio exceeded unity, the proper response from a mathematical point of view would be X. If it was less than unity, the proper response would be Y. Whether this is a good criteria for performance in the present instance is questionable since it does not take into account the correlation between adjacent stimulus variations. In any case, it is irrelevant to the present consideration since the interest here is in the perceptual process rather than mathematical solutions.

Nor can a criteria be established on the basis of "rational judgment" since "rational judgment" is a quality that cannot be defined in the present context. One cannot even say if a subject receives more reinforcement than another subject, that the first subject is behaving more rationally than the second. It may be only that he has adopted a set of assumptions that happen to be useful to the solution of the problem having the parameters described here. The same set of assumptions could prove completely inadequate for another problem. Rational behavior would probably involve the use of assumptions that would have application to a wide range of possible problems. As an illustration, the cues given in the present problem were random samples from prescribed probability distributions. If one assumed that this was the case, one would have greater success than if one assumed that the distributions were, or could have been, undergoing change through time. Yet by and large the latter assumption will fit more of the real problems of existence than will the former. In effect one subject would give equal weight to all happenings, regardless of their order of occurrence. The other subject would magnify the more recent occurrences. In the present problem, such a solution would incur a penalty.

The analysis shown below is a result of having tried to fit numerous ideas to the data. Most of these concepts, as they were represented in the model's development, were without predictive effectiveness and were dropped from further consideration. It is to be recognized, notwithstanding, that the absence of predictive effectiveness may not reflect upon the concept so much as upon the way it was tested or otherwise represented in the evaluation of the model.

Model building is a game for which there are few rules either to follow or to avoid following. It was felt, however, that certain restrictions should be placed on the present analysis. First, it was believed that each term or operation of the model should have some understandable or rational basis for being included. In other words, insertion could not be made simply to obtain a better curve-fitting result.

The second rule applied to the analysis was the Law of Parsimony. In addition to the usual admonition that one treatment or manipulation was to be preferred to the use of two or more treatments, this rule specified that the same basic model had to be made to apply to all subject classes and to all time intervals. Thus, the numerical coefficient or the power of a term could be varied if there was some logical reason for doing so (other, of course, than making it fit the data better), but the general function had to be the same for all subject and situational classes.

As stated above, a number of ideas were tried out. Since they did not prove effective, they are mentioned only in passing. One idea seemed to have some validity, but this could never be shown to a degree that would justify its inclusion. It related to the question of whether subjects learn relatively more from those trials in which they receive reinforcement (knowledge of results confirming the appropriateness of their response), as compared to those trials receiving non-reinforcement (knowledge of results confirming the appropriateness of the response not made). An individual subject analysis was made comparing the subsequent effect of (1) reinforced trials, (2) non-reinforced trials, and (3) both reinforced and non-reinforced trials. The only thing that can be said with certainty from this work is that both reinforced and non-reinforced trials effect a change in behavior. It was impossible to tell which of the two circumstances had the greater influence. There was perhaps some evidence that normal subjects obtained more relative benefit from non-reinforced trials than did the retarded, but the differential effect was not strong enough to deserve inclusion in the model.

A second concept that was investigated was on whether subjects respond selectively to stimulus cues. For example, would a particular subject respond to the position of the arms but ignore the position of the head and legs during the early stages of testing? Although this type of behavior seemed to be occurring in some individuals, the evidence was not good enough to support the inclusion of the variable in the model. This was true despite the verbal reports of subjects that this was their method of responding. A succession of progressive correlations were run on a number of individuals, and while the effect was noticeable, it was never strong enough or consistent enough to improve the model by taking notice of such differentiation. To some extent this difficulty was likely to have been due to the testing procedures employed. Refinement of the model would thus depend upon some difference in the method of acquiring data.

In a previous research effort (1964) Elam and Duke found some value in the following estimates of stimulus generalization:

$$G_L = R - (S_R - S_G)$$

$$G_S = \sqrt{R^2 - (S_R - S_G)^2}$$

$$G_H = R - \sqrt{R^2 - [R - (S_R - S_G)]^2}$$

where R is the stimulus range measured by the number of subjectively equal stimulus variations while S_R is the number assigned to the reinforced stimulus variation and S_G the number assigned to the stimulus variation being generalized upon.

G_L, G_S and G_H were used to designate the linear, the positively accelerated, and the negatively accelerated decreasing functions which were estimates of the degree of transmissions of effect from the stimulus variation given knowledge of results to all other stimulus variations of that one continuum.

Using a series of coefficients on these formulas, it was shown that no one would simultaneously satisfy the data from all three of the subject groups as well as would the function finally adopted. On the authority of the Law of Parsimony, these were dropped from further consideration. Perhaps, not surprisingly, the function that was found to best satisfy all of the data was the familiar phi gamma or normal curve. It is this function that is used in the analyses described below. G_1, G_2 and G_3 all refer to the same curve, but with $\sigma = 1$ applied to G_1, $\sigma = 2$ applied to G_2, and $\sigma = 3$ applied to G_3. The sigma values were obtained from the just noticeable difference scale which resulted from a tachistoscopic presentation of the variables in a separate pilot study. Thus, G_1 is relatively leptokurtic, while G_2 is mesokurtic and G_3 platykurtic. Another way of saying this is that if G_1 proves to be the best estimate (as it did for the college group), then the effect of knowledge of results concerning one cue variation is not irradiated to other variations nearly to the extent that would be the case if G_3 (as turned out to be the case with the retarded) were the best estimate for the group.

In the previously referenced study, four estimates of stimulus synthesis were examined. The formulas appear below:

1. Square Solution

$$I_S = \frac{P^2_{X_A} + P^2_{X_B} --- P^2_{X_N}}{P^2_{X_A} + P^2_{X_B} +--- P^2_{X_N} + P^2_{Y_A} --- P^2_{Y_N}}$$

According to this formula the probability of a picture being responded to as an X (I_S) is obtained by summing the square of the probabilities of it being judged as an X based upon the separate cues (A, B --- N) divided by this sum plus the individual probabilities squared of it being judged as a Y.

2. Geometric Solution

$$I_G = \frac{\sqrt[N]{P_{X_A} \cdot P_{X_B} \text{ --- } P_{X_N}}}{\sqrt[N]{P_{X_A} \cdot P_{X_B} \text{ --- } P_{X_N}} + \sqrt[N]{P_{Y_A} \cdot P_{Y_B} \text{ --- } P_{Y_N}}}$$

3. Linear Solution

$$I_L = P_{X_A} + P_{X_B} + \text{---}\ P_{X_N} \;/\; P_{X_A} + P_{X_B} + \text{---}\ P_{X_N} + P_{Y_A} \text{ --- } P_{Y_N}$$

4. Log Solution

$$I_{Log} = \frac{\mathrm{Log}_{10} \quad (P_{X_A} \cdot P_{X_B} \text{ --- } P_{X_N})}{\mathrm{Log}_{10} \quad (P_{X_A} \cdot P_{X_B} \text{ --- } P_{X_N} \cdot P_{Y_A} \text{ --- } P_{Y_N})}$$

These formulas had varying success in the prediction of normal and retarded groups. It was decided in the present effort, however, to work with variations on a single model. Since the Linear and Square solutions had been generally successful in the earlier study, it seemed reasonable to use the general form:

$$I = P^{\phi}_{X_A} + P^{\phi}_{X_B} \text{ --- } P^{\phi}_{X_N} \;/\; P^{\phi}_{X_A} + P^{\phi}_{X_B} + \text{---}\ P^{\phi}_{X_N} + P^{\phi}_{Y_A} + \text{---}\ P^{\phi}_{Y_N}$$

where $P^{\phi}_{X_A}$ is the probability of the stimulus being judged an X based upon the cue raised to the ϕ power. The only variation made upon this general model was the value of ϕ .

Another factor to be considered is the growth of the potential of an individual cue to elicite a response. This growth relates to the ratio of its magnitude to its theoretical limit. Most learning curves suggest that the growth of a habit is inversly related to its momentary probability of occurrence. If at a given moment in the history of an organism the probability of stimulus S to elicit response R_1 is P_1, and if its probability of eliciting R_2 is P_2, and if $P_1 > P_2$, then Δ 2 (the effect of reinforcing R_2) will be greater than Δ 1 (the effect of reinforcing R_1).

The growth in the probability of the occurrence of a response is not a simple inverse function of its momentary probability. It is evident that, as training progresses, reinforcing events become less and less effective in modifying behavior. The predisposition to perceive in a given way exhibits more and more enertia as experience is accumulated. At the beginning of a test sequence a single event can have a great deal of influence on the behavior of a subject. The same event would be much less effective later in testing even if the ratio P_1/P_2 were equal for the two situations.

Although occurrences early in testing have a predominant effect on the development of perceptual organization, their influence is, nevertheless, limited. If, before testing commences, the probability of R_1 is equal to the probability of R_2, one might think that reinforcing one or the other would shift the probability value completely in its favor. Although there is a tendency in this direction, it must be said that this is not usually the result.

With the preceding facts and findings in mind, the model was developed to include the following:

I - An analysis of the changing effects of each separate cue. These were to be expressed as momentary probability values.

Ia - The probability value of a cue to elicite an X response was determined from the ratio of its momentary "X strength" to its "X strength" plus its "Y strength."

Ib - The "X strength" of a cue variation was obtained from the three following sources:*

1. Some initial value that existed before testing. It was assumed that the "X strength" was equal to the "Y strength" for this factor. This initial strength was included to account for the fact that subjects are not absolutely predisposed to act on the second trial completely on the basis of what happened on the first trial, even if the stimulus variables are identical.

2. Some value accrues from each direct identification that the picture in which the cue occurs is an X or a Y.

3. Some value accrues from each indirect identification (stimulus generalization).

Ic - It was assumed that the effect of any trial decayed as a log function of the number of intervening trials.

II - The effect of the conjoinment of cues was predicted for X as a function of the summed probabilities of each cue raised to some common power. This is shown as I ϕ above.

Fifteen variations on the model were evaluated. These were made up on the basis of three sigma values for the stimulus generalization curve ($\sigma = 1$, 2 or 3 just noticeable units of stimulus difference), and five integration formulas in which the power to which the single cue probabilities were raised were varied from one to five.

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* After several adjustments, the relative value of the initial value to the value obtained from each direct identification was made equal. The value of the indirect identification (stimulus generalization) followed the ordinate of the normal curve with σ based upon the equal interval stimulus scale of the cue.

RESULTS

The results of the analysis are shown in Figures 5 through 46. G_1, G_2 and G_3 refer to the sigma value of the generalization curve, while P_1, P_2, P_3, P_4 and P_5 reference the power to which the single cue probability estimates were raised. Figures 5 through 19 are presented as an index of the absolute difference between the proportion of subjects responding X to the proportion that was predicted would respond X from the variations of the model. Thus, for each trial within the block (50 trials), the absolute difference d between the proportion empirically obtained (P_O) and the proportion expected (P_E) was calculated $d = \sqrt{(P_O - P_E)^2}$. The means of these values were then obtained $d = \Sigma d/50$. It will be seen in Figures 5, 6 and 7 that the P_1 solution is most representative of the retarded group. The solution was not especially good for the grade school group and even less for the college students. Little difference for the retarded group is evident between the generalization solutions, although the G_1 solution is quite evidently better for the grade school and college groups.

Figures 8, 9 and 10 show the P_2 solution for these generalization formulas. A crossover is very evident here with the best prediction being made for the grade school students with the G_3 and G_2 formulas.

The prediction of the retarded group has become inexact.

In Figures 11, 12 and 13 the trend continues. Now, however, the college group conforms most exactly to the prediction. There is also evidence that the G_1 formula is most precise for this population.

In Figures 14, 15 and 16 the trend becomes stabilized. This appears to be the best solution for the college students.

In Figures 17, 18 and 19 the curves for the college students seem to be increasing. This indicates that passage has been made through the best solution.

Another way of examining the accuracy of prediction is by taking the algebraic difference between prediction and result. This is shown in Figures 20 through 34. The algebraic differences between actual and predicted results show the systematic variance that the model does not account for. This has been done only for Trial Blocks 1 (Trials 1-50), 4 (Trials 151-200), and 8 (Trials 351-400). These are an interesting contrast to the previous figures. Except for the retarded group, the model shows a growth in systematic error for the latter part of training. This is especially true for the grade school students. Something is occurring that the model does not account for.

A third method of illustrating the degree of accuracy of the model is by correlating the expected to the obtained response frequencies. These are shown in Figures 35 through 46. Here the correlations for the retarded are relatively low, while those for the college students are consistently high.

DISCUSSION

Considering the nature of the indexes used, the model appears to be an extremely good predictor of normal behavior. A small amount of systematic behavior is unaccounted for, however, as witnessed by the algebraic error curves. From these same curves it can be deduced that although the prediction on the retarded is not as good as for the normals, there is little that can be done to improve the situation within the range provided by this model. Improvement must, therefore, lie in some form of individual analysis that was not made possible using the present procedures.

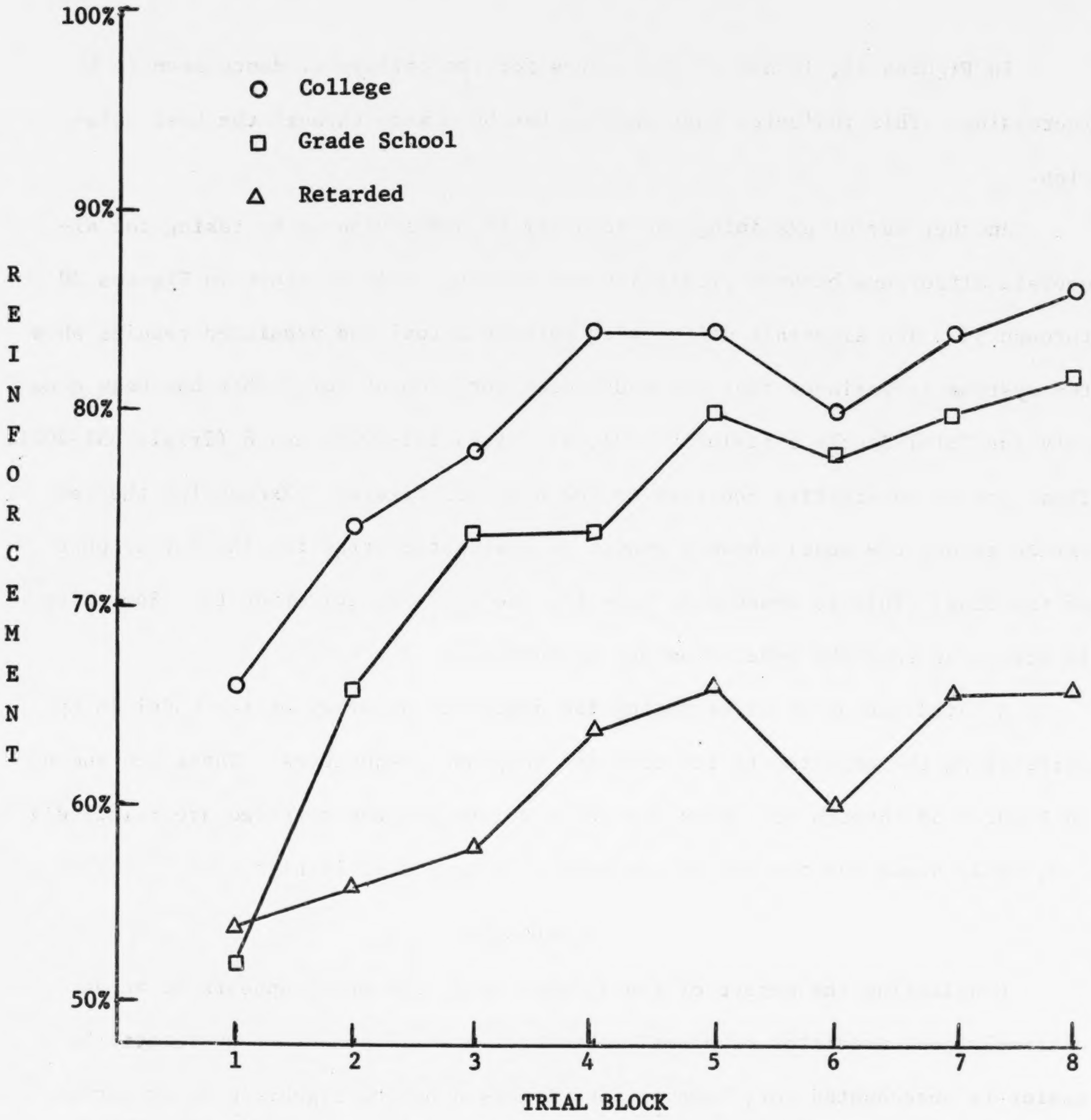


Fig. 4. Mean percentage of reinforcement for the three groups as a function of trial block. Each block consists of 50 trials.

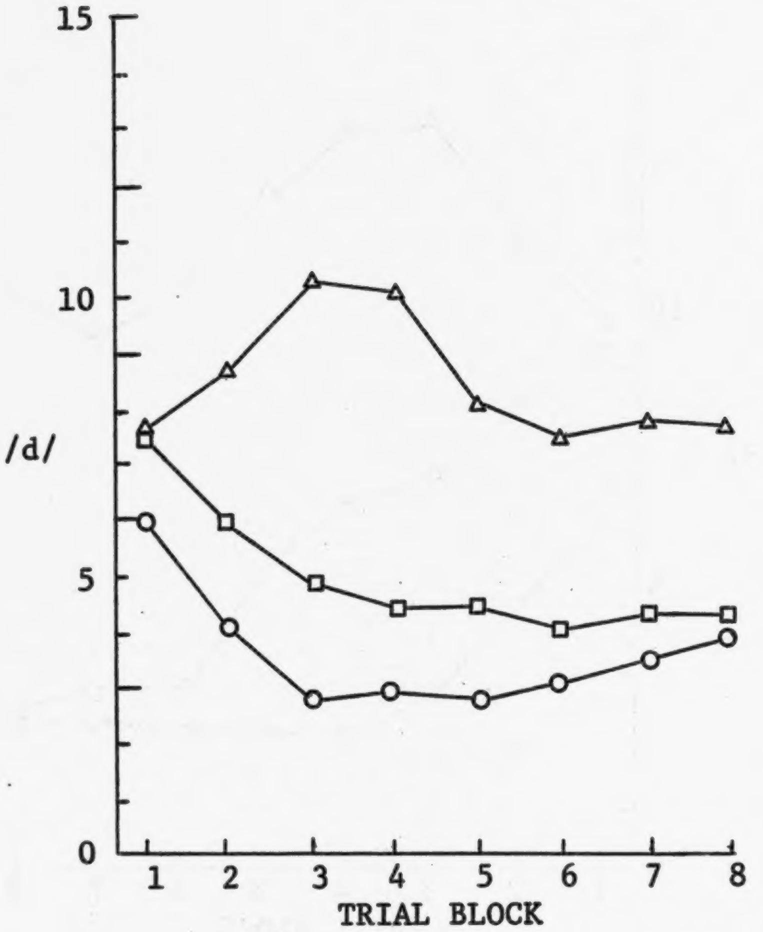


Fig. 11. Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P3 Solution.

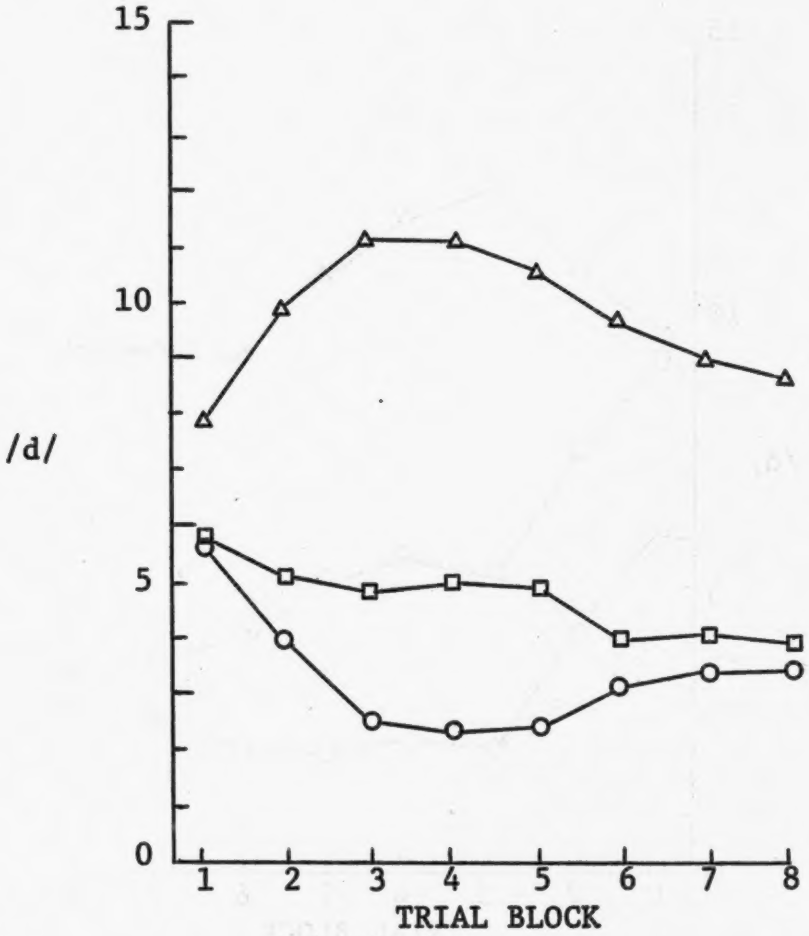


Fig. 12. Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P3 Solution.

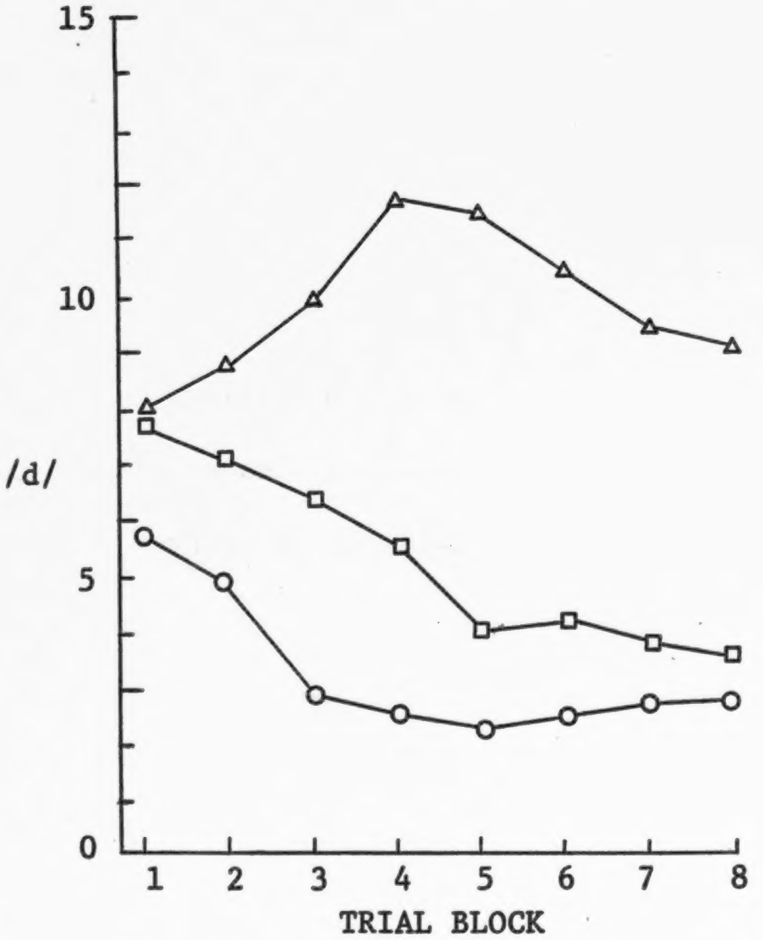


Fig. 13. Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P3 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

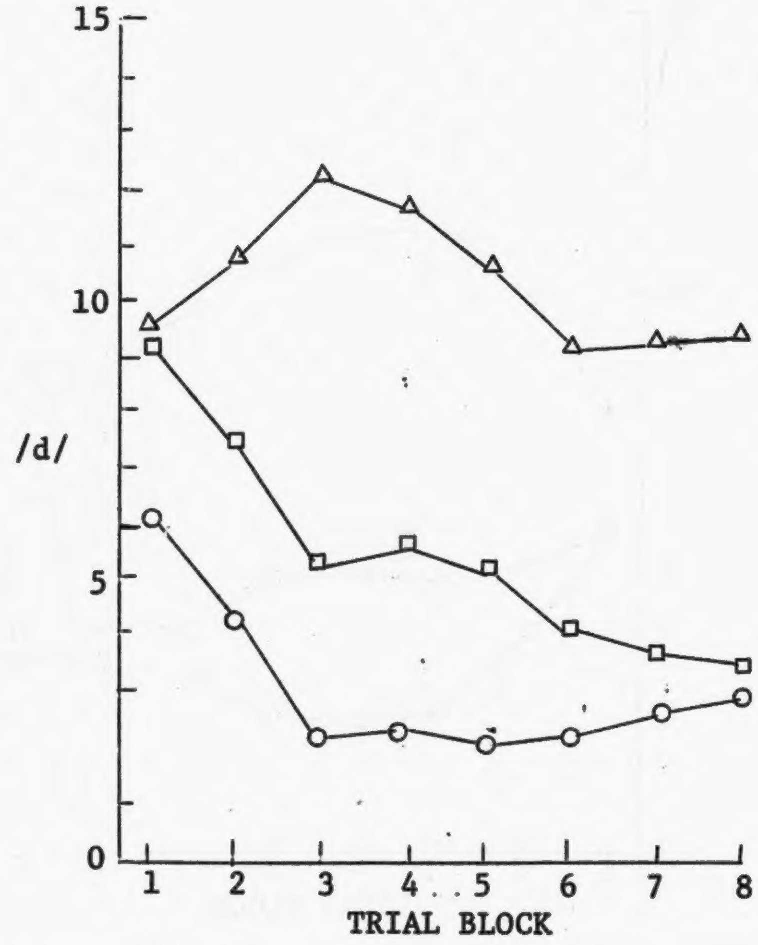


Fig. 14. Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P4 Solution.

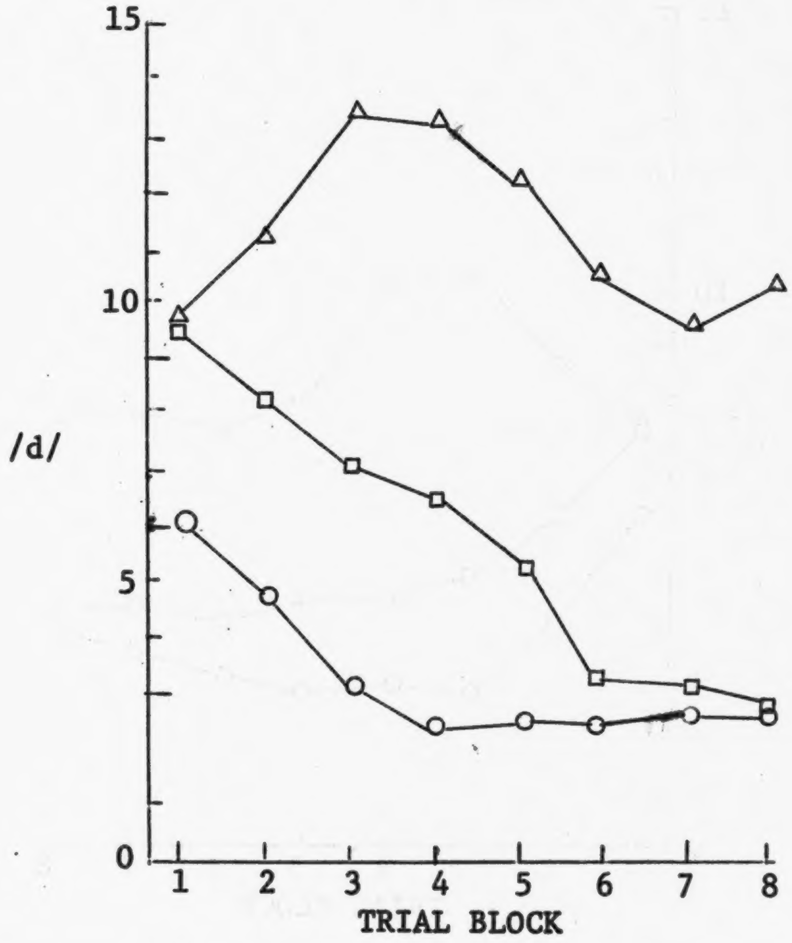


Fig. 15. Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P4 Solution.

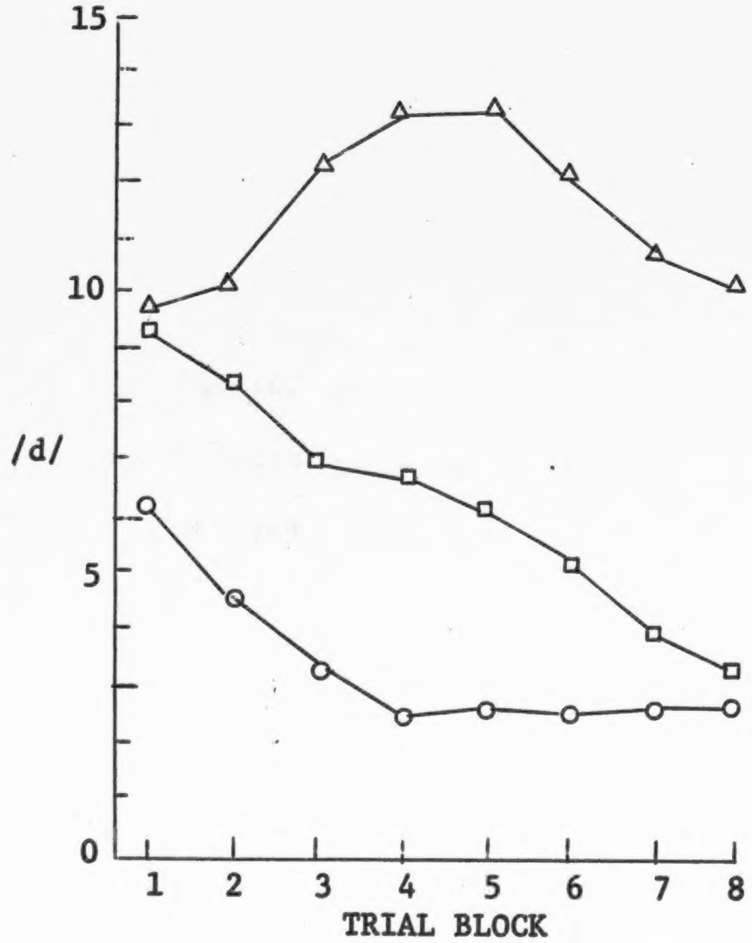


Fig. 16. Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P4 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

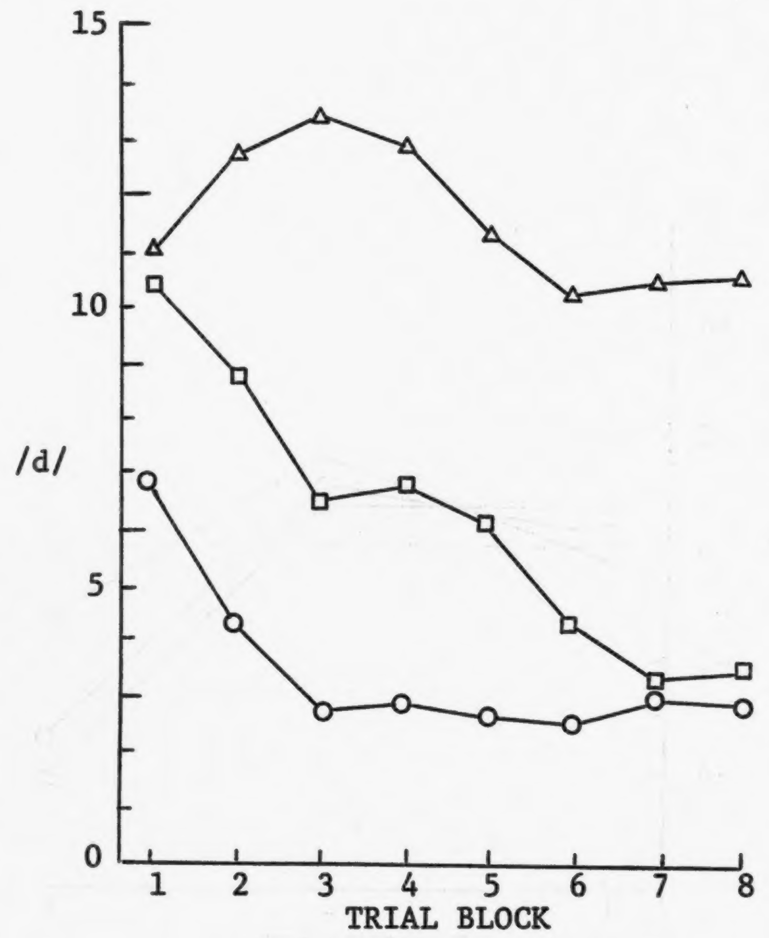


Fig. 17. Mean absolute difference /d/ between empirical data and predicted results based upon the G3, P5 Solution.

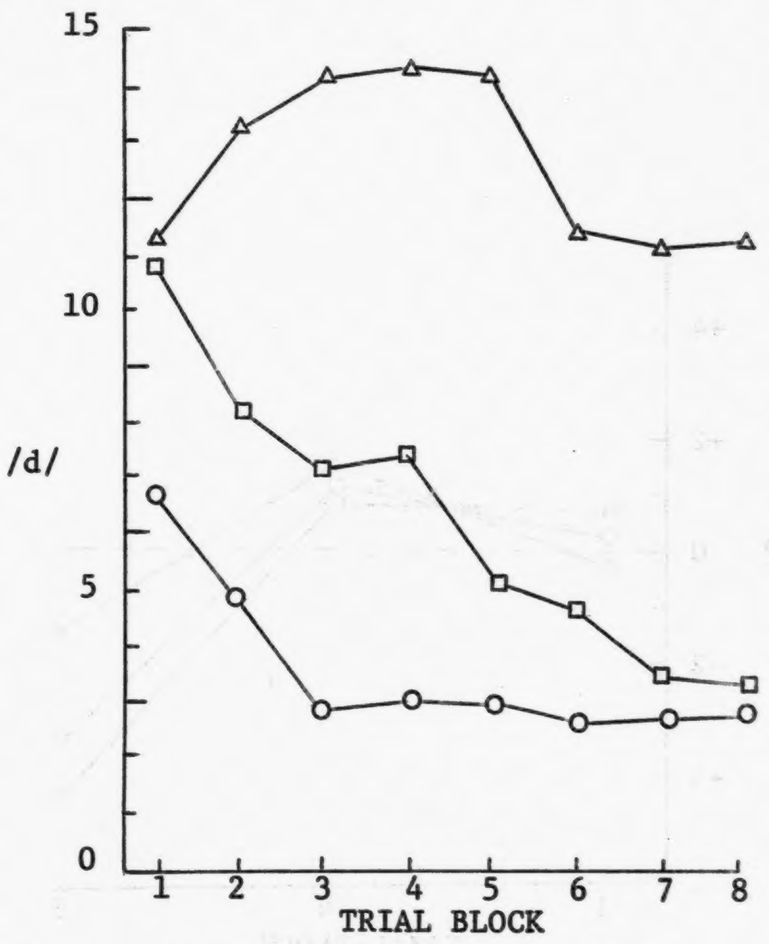


Fig. 18. Mean absolute difference /d/ between empirical data and predicted results based upon the G2, P5 Solution.

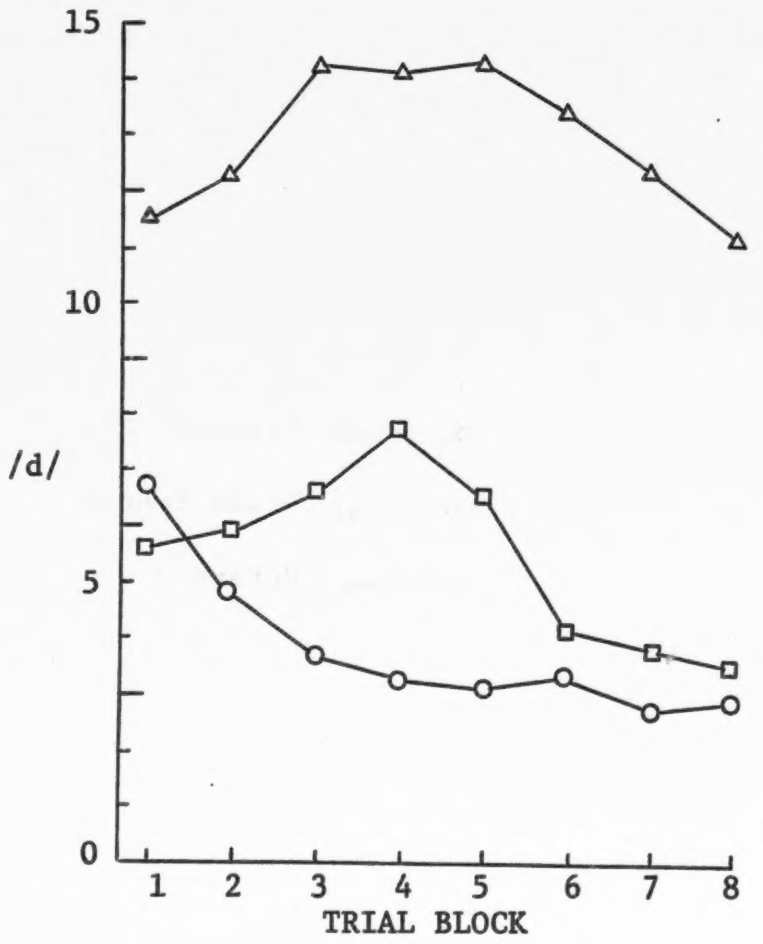


Fig. 19. Mean absolute difference /d/ between empirical data and predicted results based upon the G1, P5 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

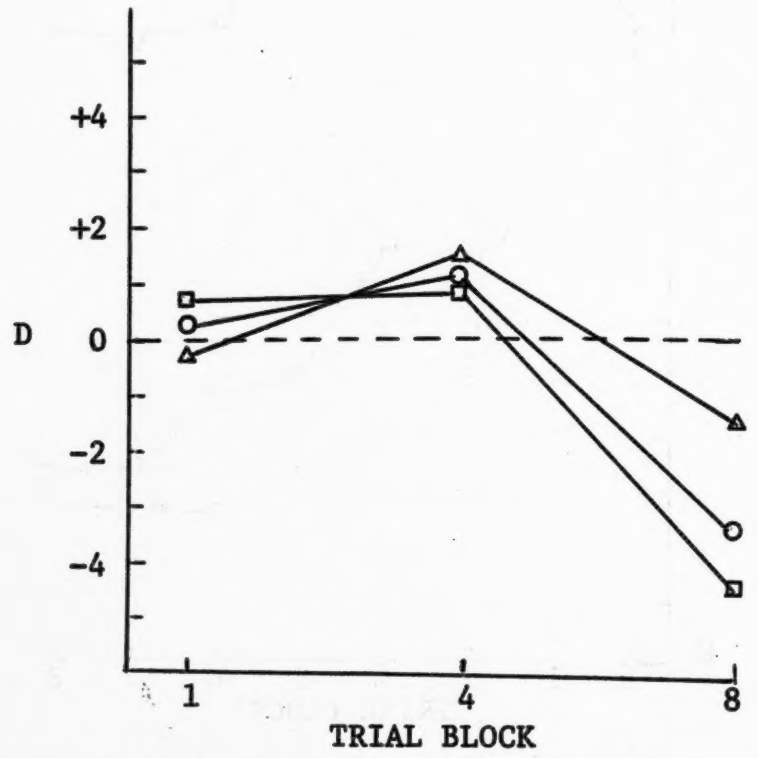


Fig. 20. Mean algebraic difference D between empirical data and predicted results based upon G3, P1 Solution.

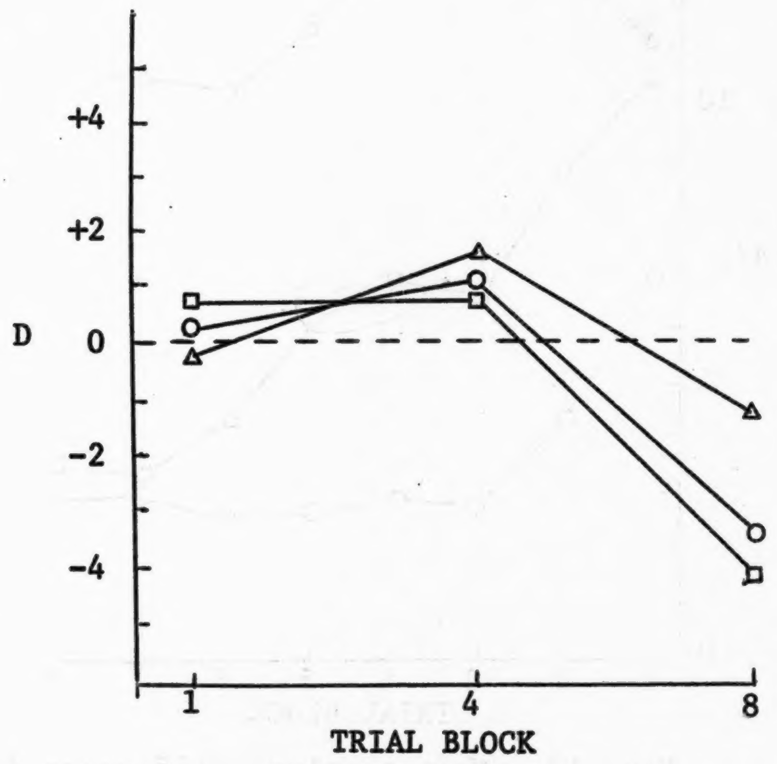


Fig. 21. Mean algebraic difference D between empirical data and predicted results based upon G2, P1 Solution.

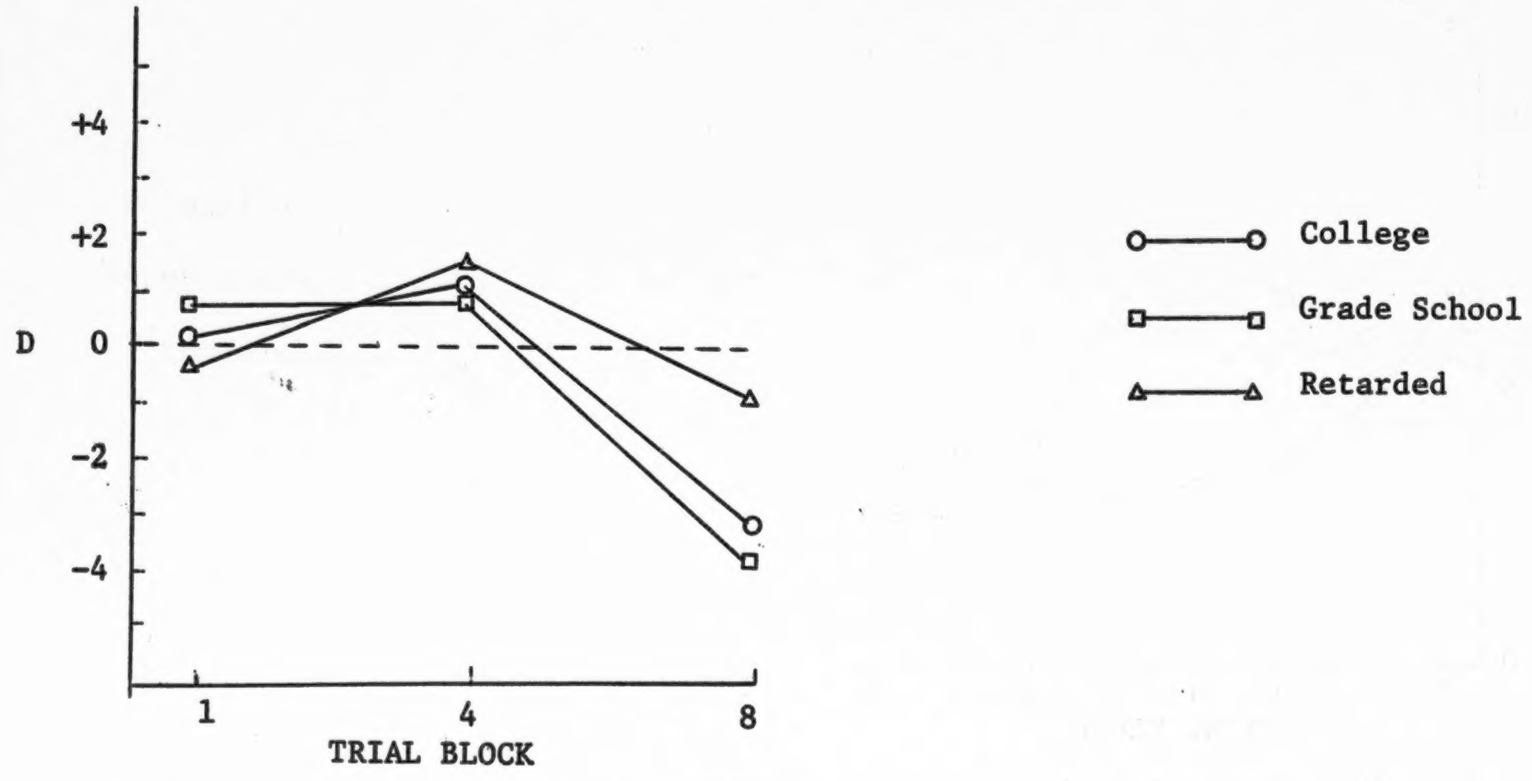


Fig. 22. Mean algebraic difference D between empirical data and predicted results based upon G1, P1 Solution.

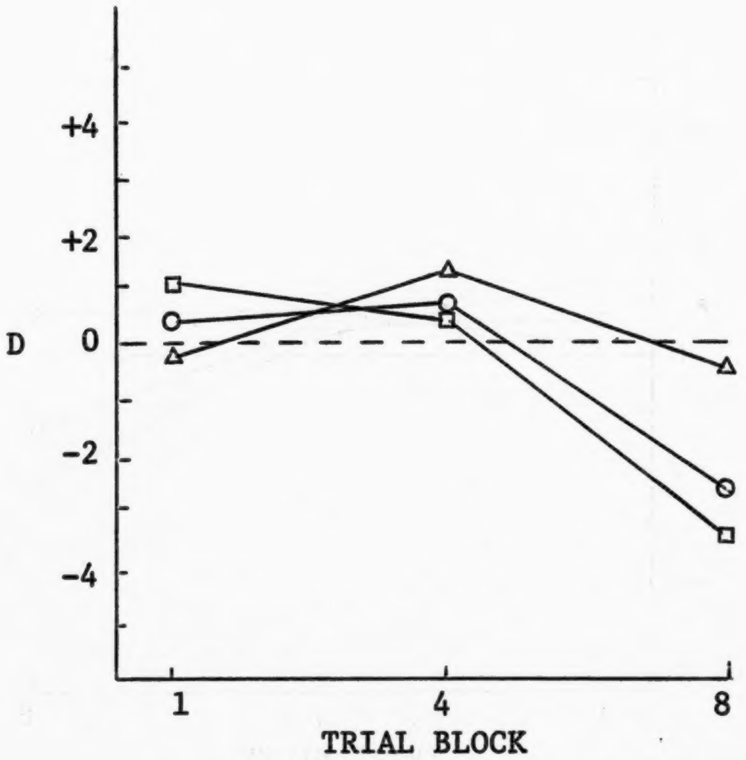


Fig. 23. Mean algebraic difference D between empirical data and predicted results based upon G3, P2 Solution.

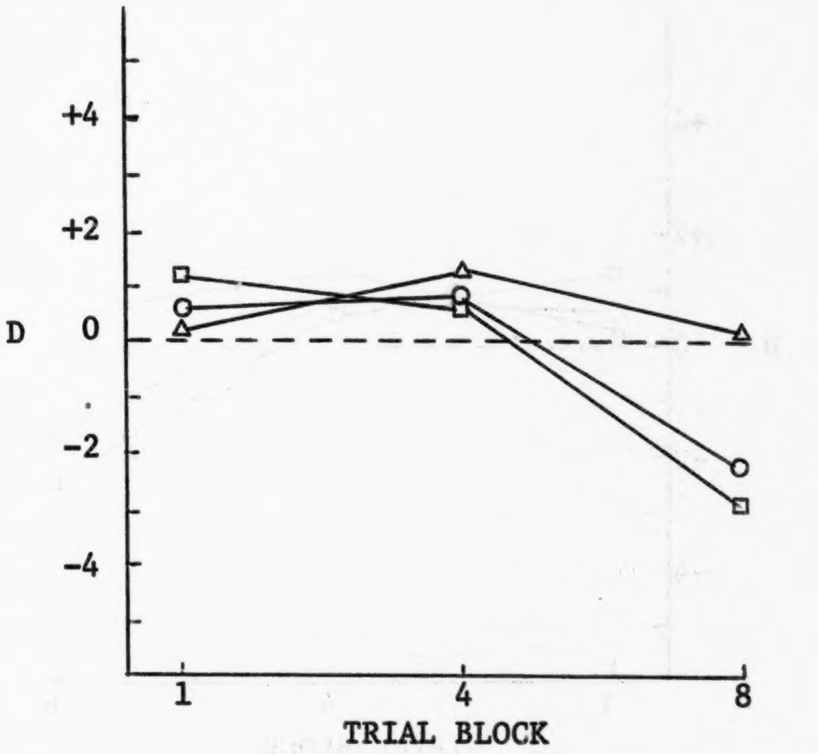


Fig. 24. Mean algebraic difference D between empirical data and predicted results based upon G2, P2 Solution.

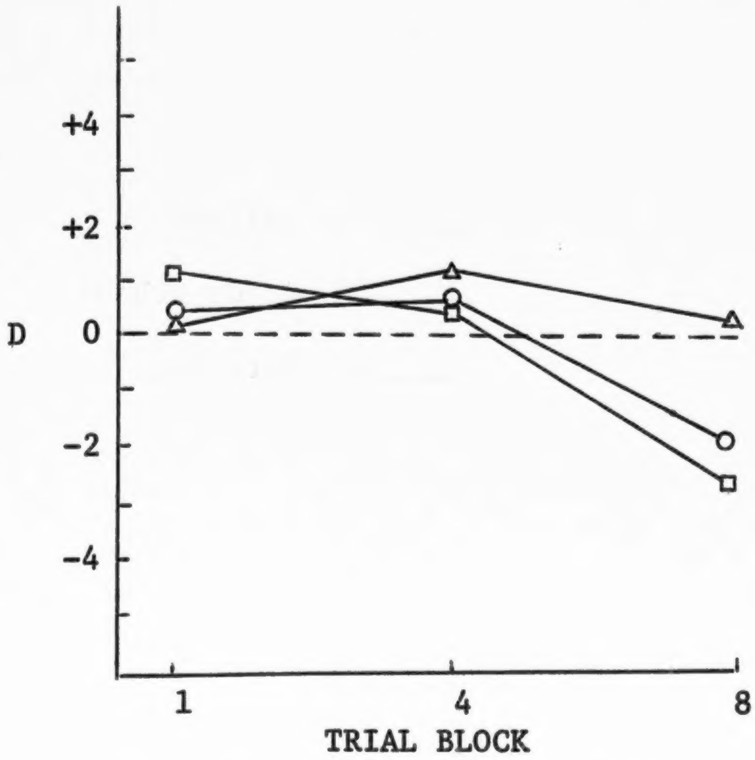


Fig. 25. Mean algebraic difference D between empirical data and predicted results based upon G1, P2 Solution.

○———○ College

□———□ Grade School

△———△ Retarded

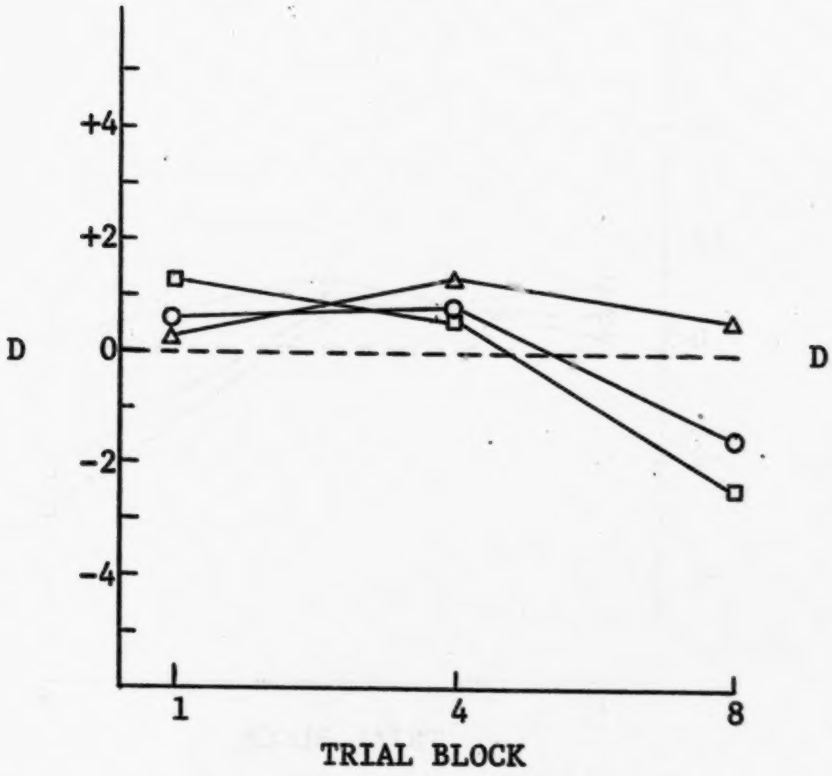


Fig. 26. Mean algebraic difference D between empirical data and predicted results based upon G3, P3 Solution.

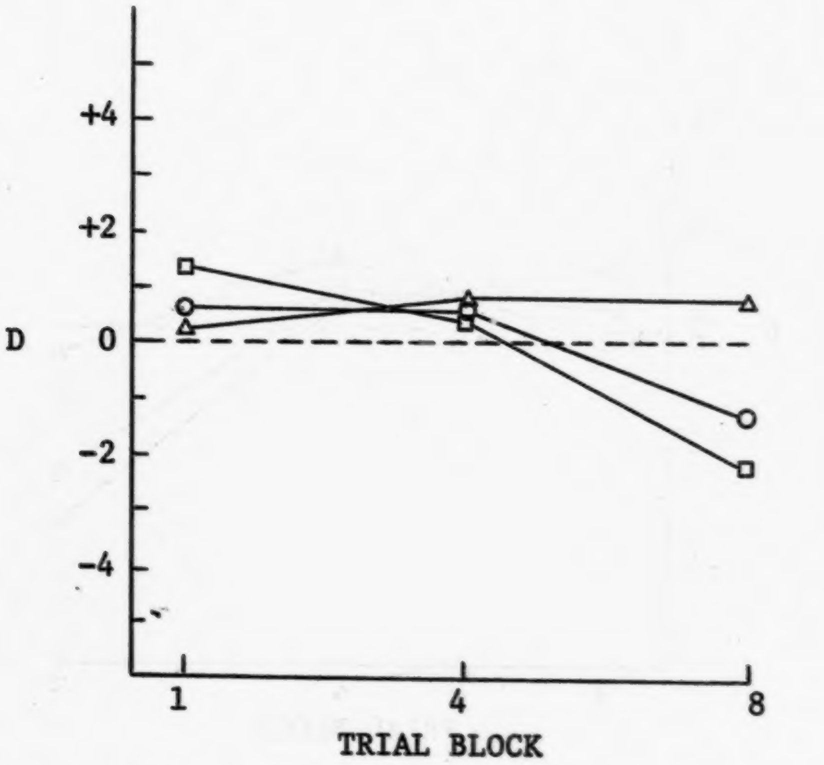


Fig. 27. Mean algebraic difference D between empirical data and predicted results based upon G2, P3 Solution.

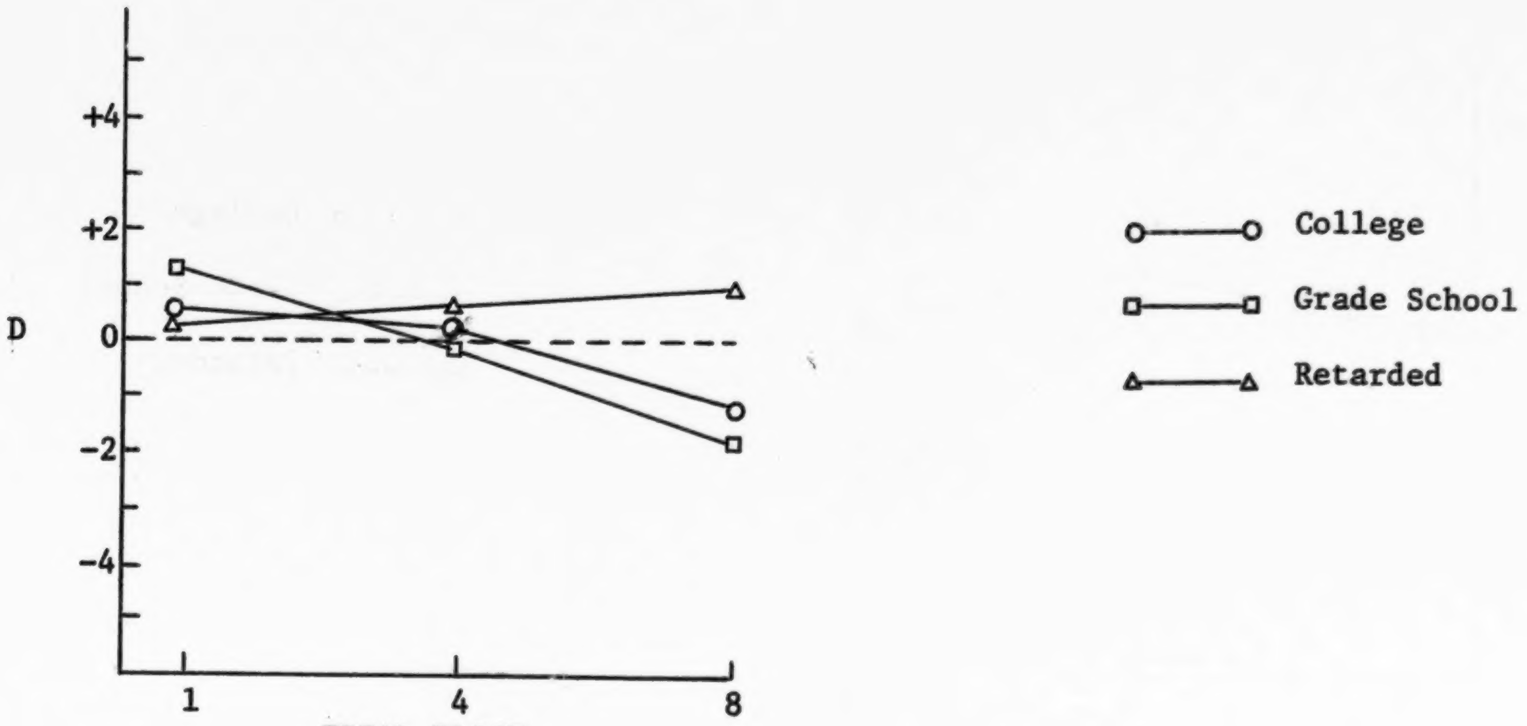


Fig. 28. Mean algebraic difference D between empirical data and predicted results based upon G1, P3 Solution.

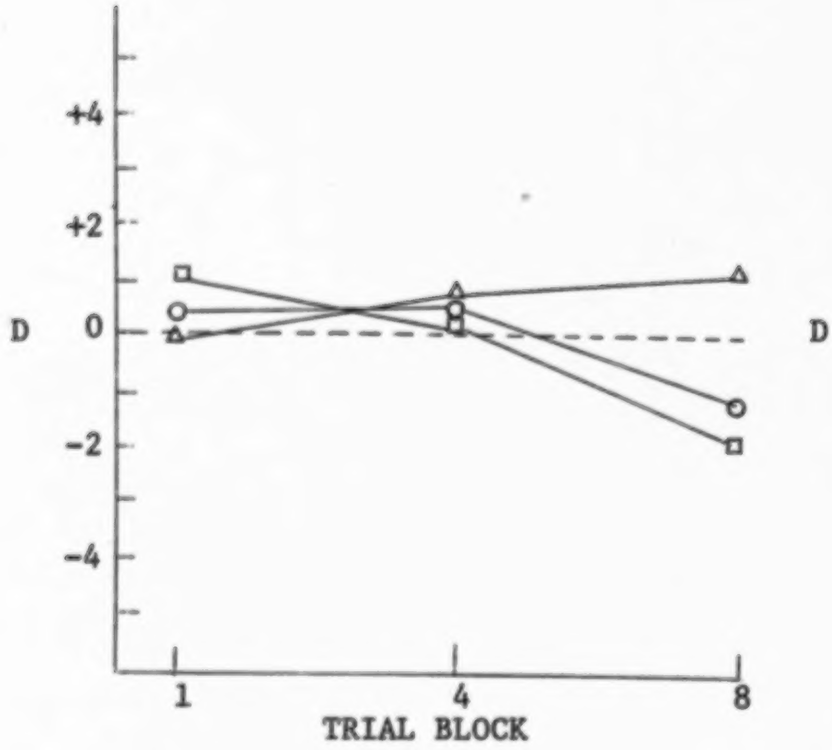


Fig. 29. Mean algebraic difference D between empirical data and predicted results based upon G3, P4 Solution.

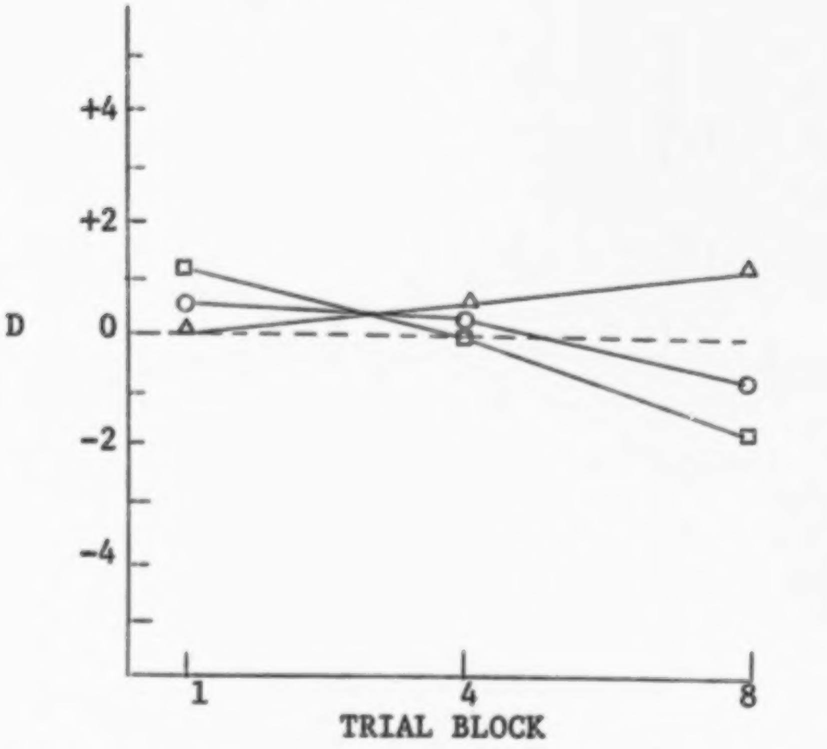


Fig. 30. Mean algebraic difference D between empirical data and predicted results based upon G2, P4 Solution.

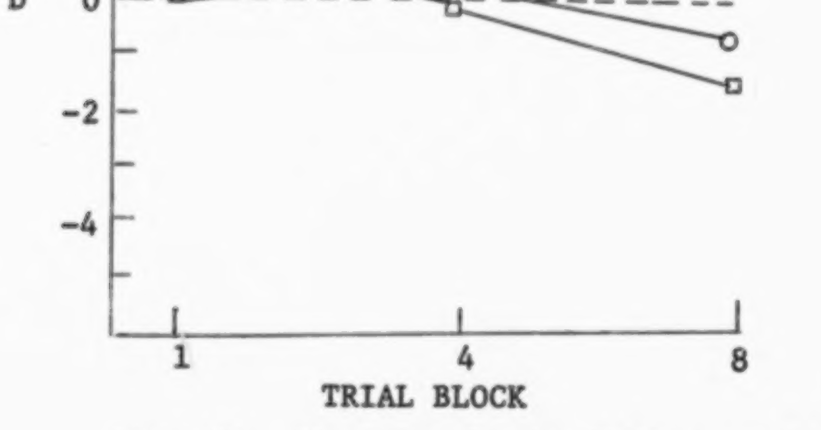


Fig. 31. Mean algebraic difference D between empirical data and predicted results based upon G1, P4 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

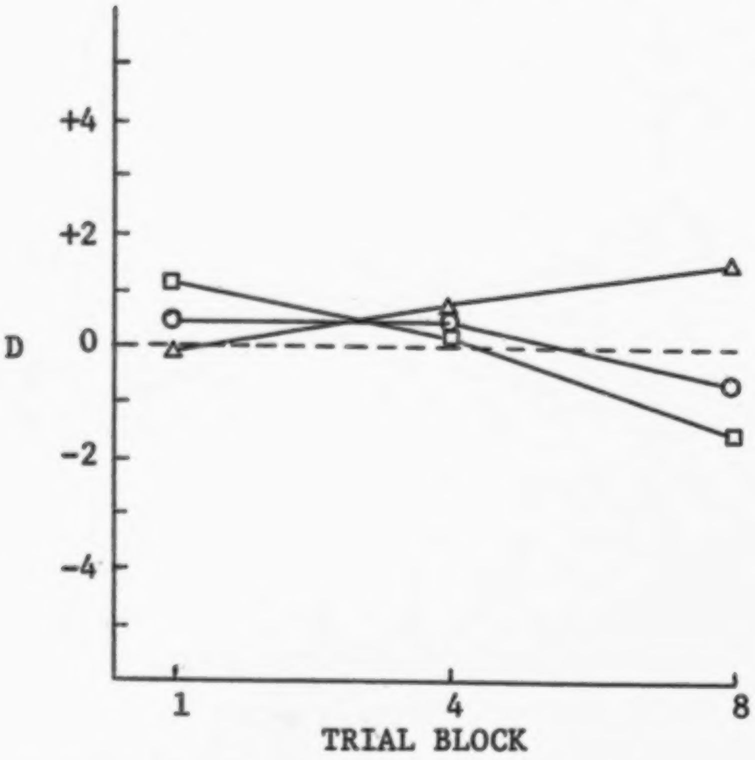


Fig. 32. Mean algebraic difference D between empirical data and predicted results based upon G3, P5 Solution.

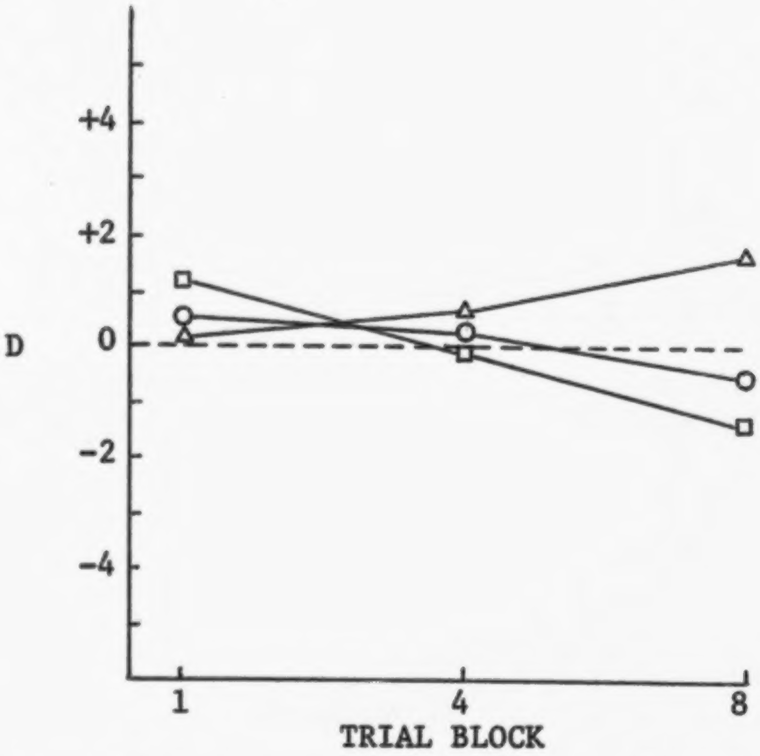


Fig. 33. Mean algebraic difference D between empirical data and predicted results based upon G2, P5 Solution.

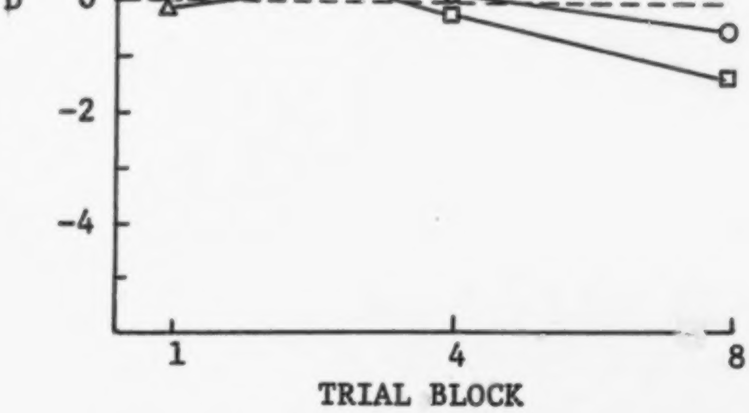


Fig. 34. Mean algebraic difference D between empirical data and predicted results based upon G1, P5 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

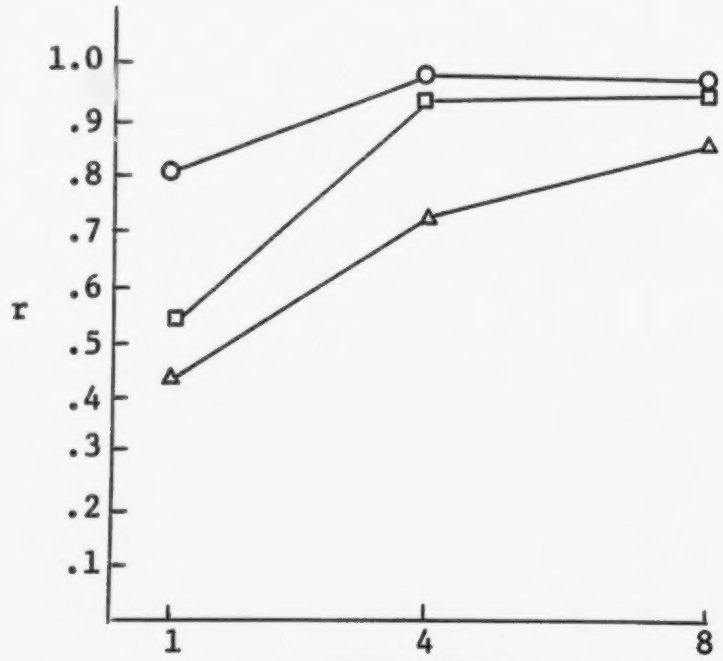


Fig. 35. Correlation r between empirical data and predicted results based upon the G3, P1 Solution.

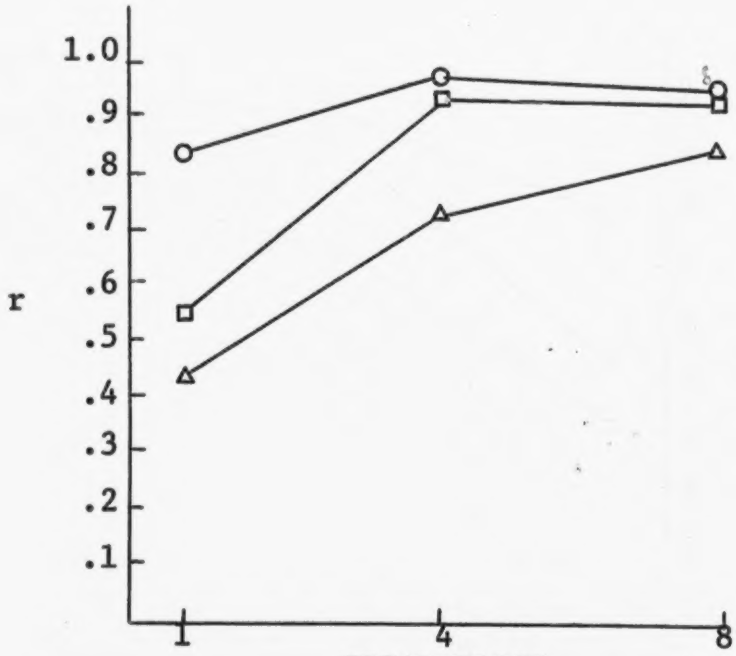


Fig. 36. Correlation r between empirical data and predicted results based upon the G2, P1 Solution.

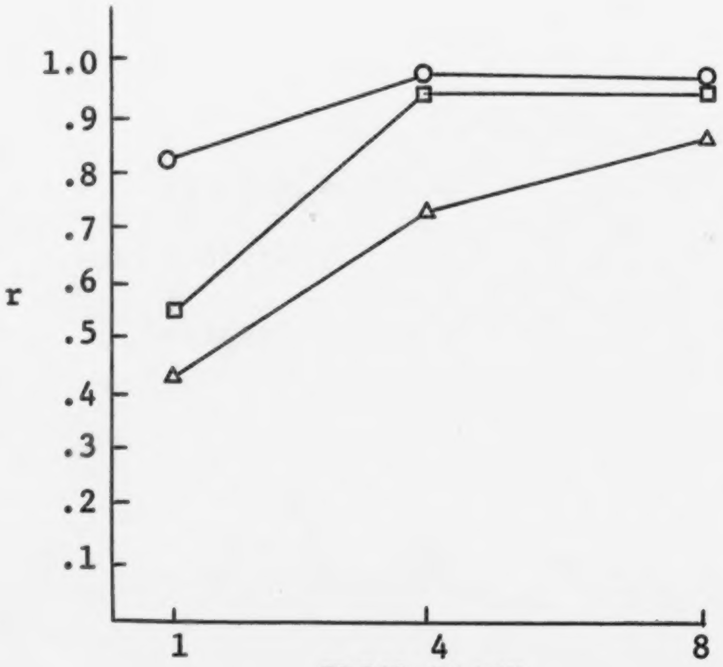


Fig. 37. Correlation r between empirical data and predicted results based upon the G1, P1 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

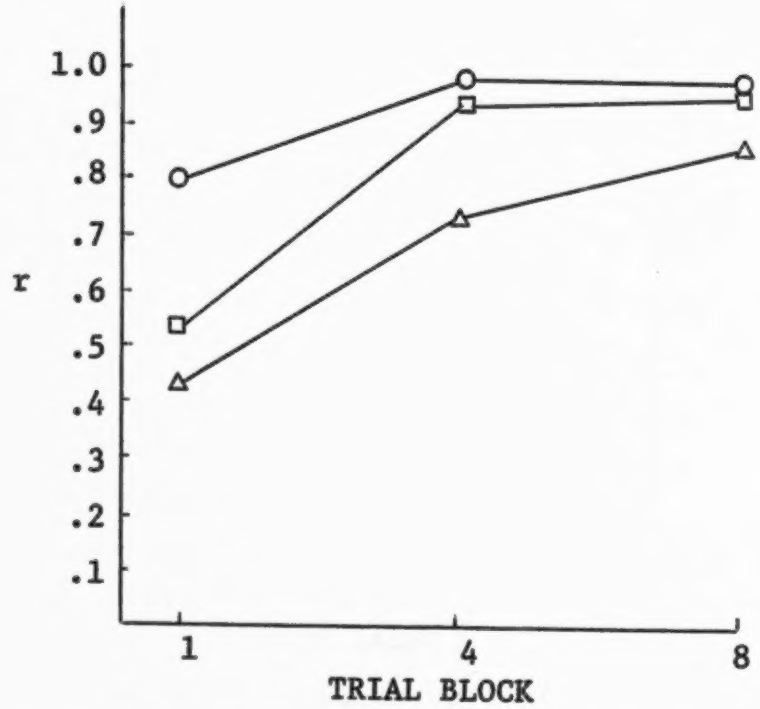


Fig. 38. Correlation r between empirical data and predicted results based upon the G3, P2 Solution.

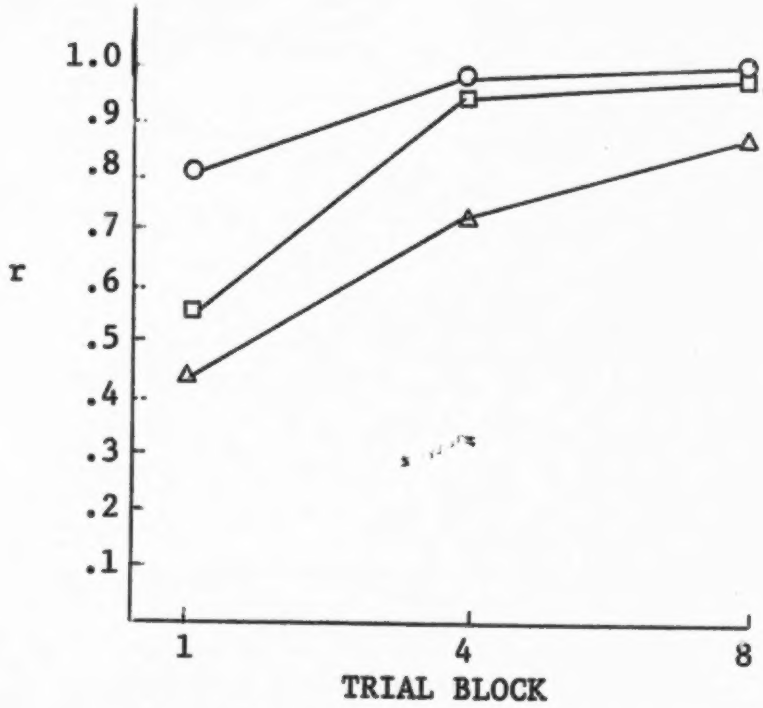


Fig. 39. Correlation r between empirical data and predicted results based upon the G2, P2 Solution.

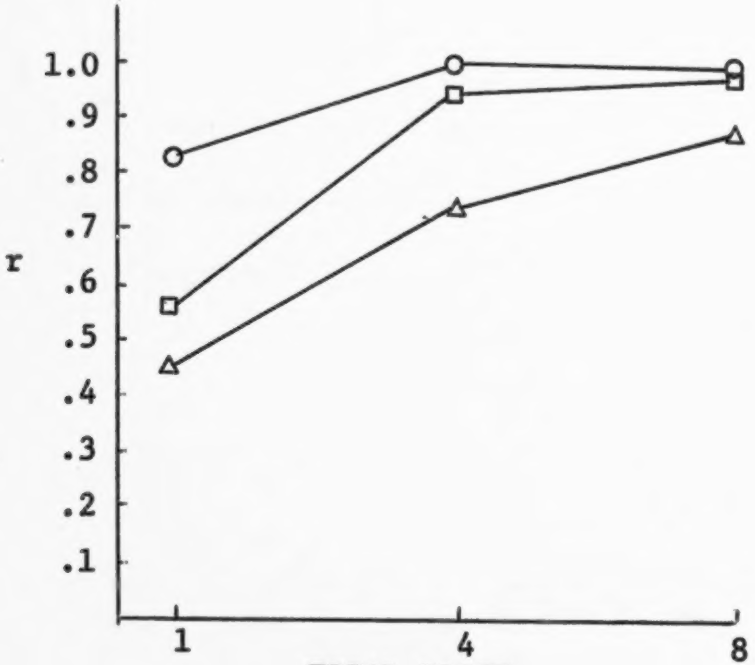


Fig. 40. Correlation r between empirical data and predicted results based upon the G1, P2 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

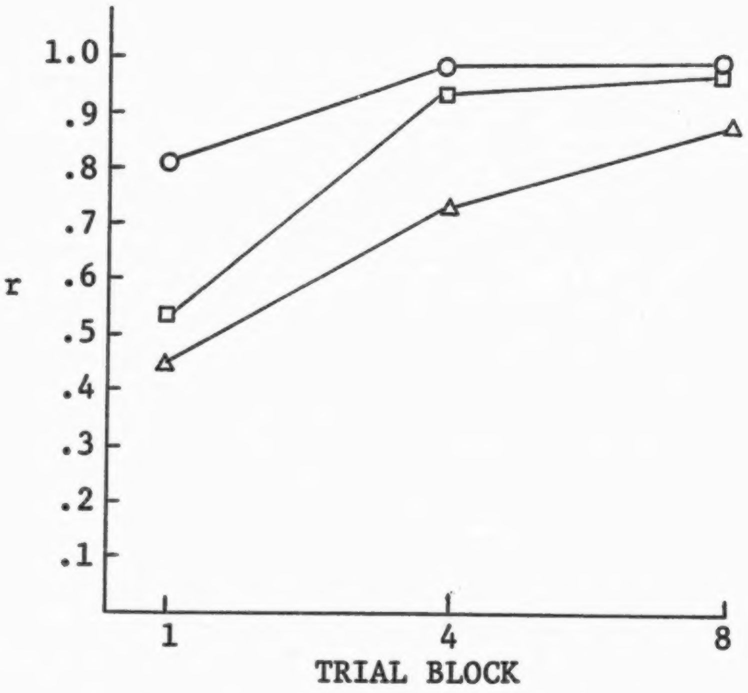


Fig. 41. Correlation r between empirical data and predicted results based upon the G3, P3 Solution.

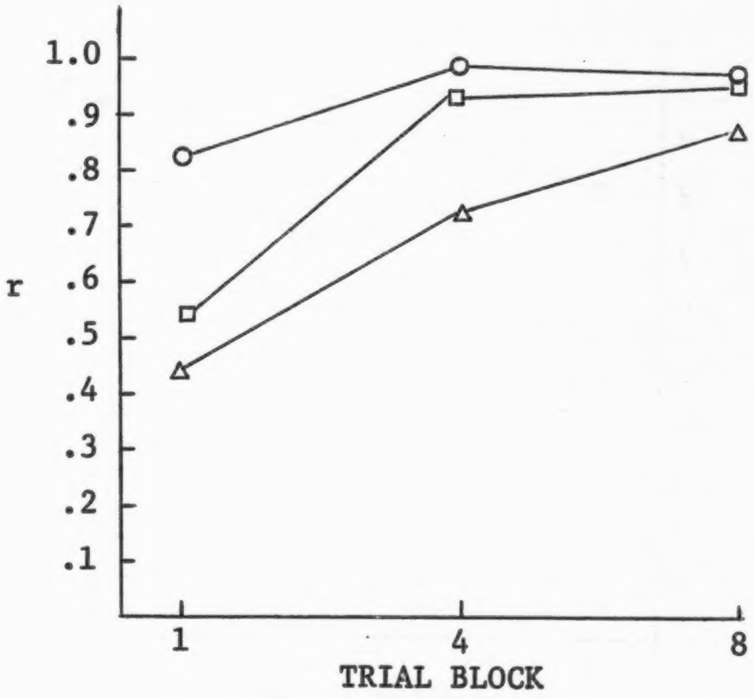


Fig. 42. Correlation r between empirical data and predicted results based upon the G2, P3 Solution.

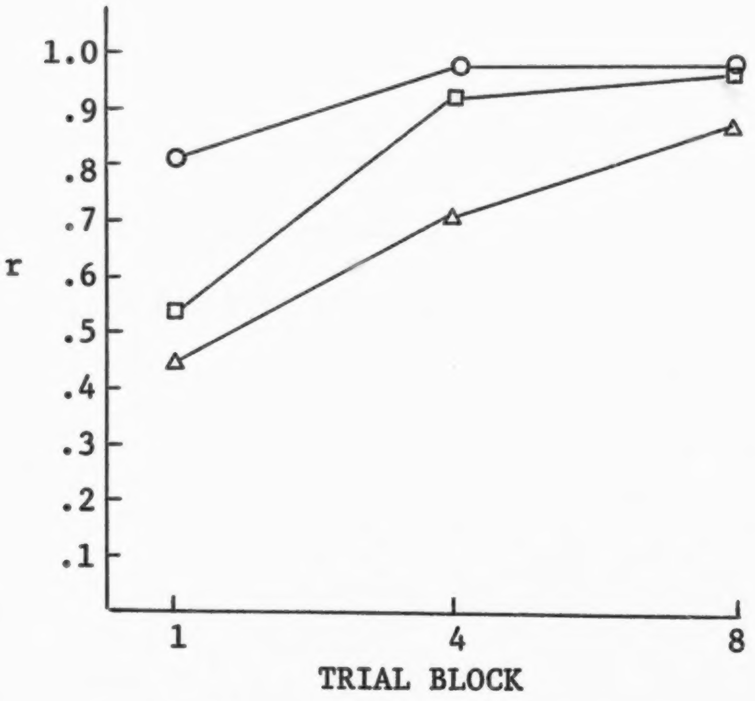


Fig. 43. Correlation r between empirical data and predicted results based upon the G1, P3 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

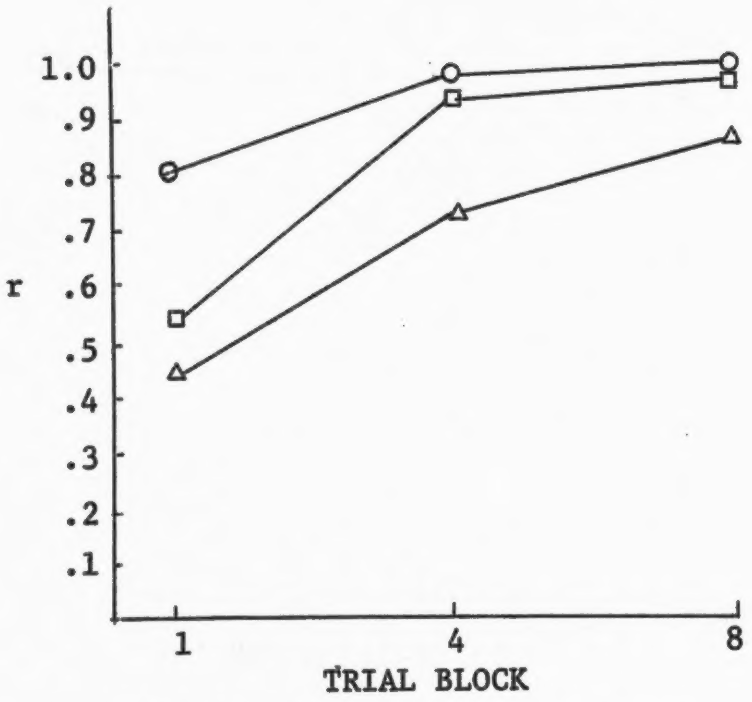


Fig. 44. Correlation r between empirical data and predicted results based upon the G3, P4 Solution.

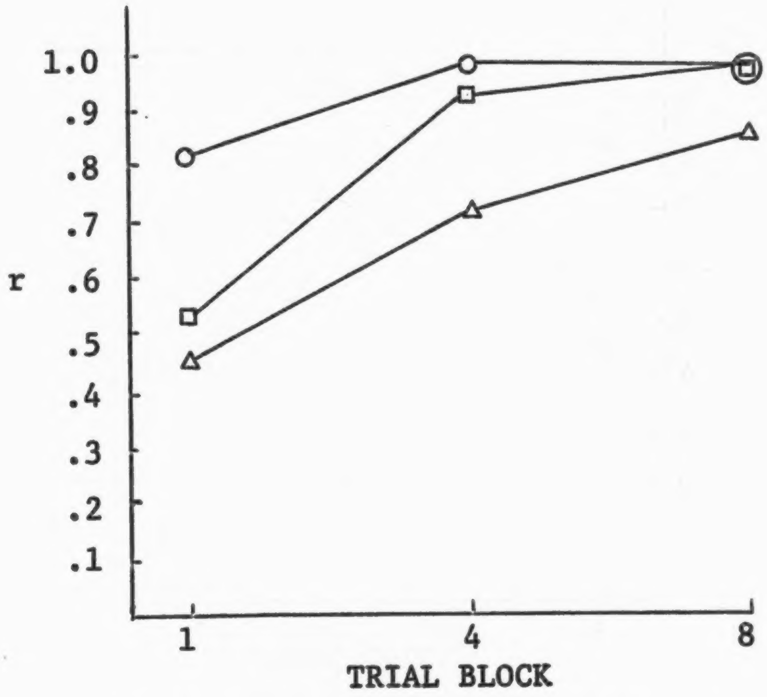


Fig. 45. Correlation r between empirical data and predicted results based upon the G2, P4 Solution.

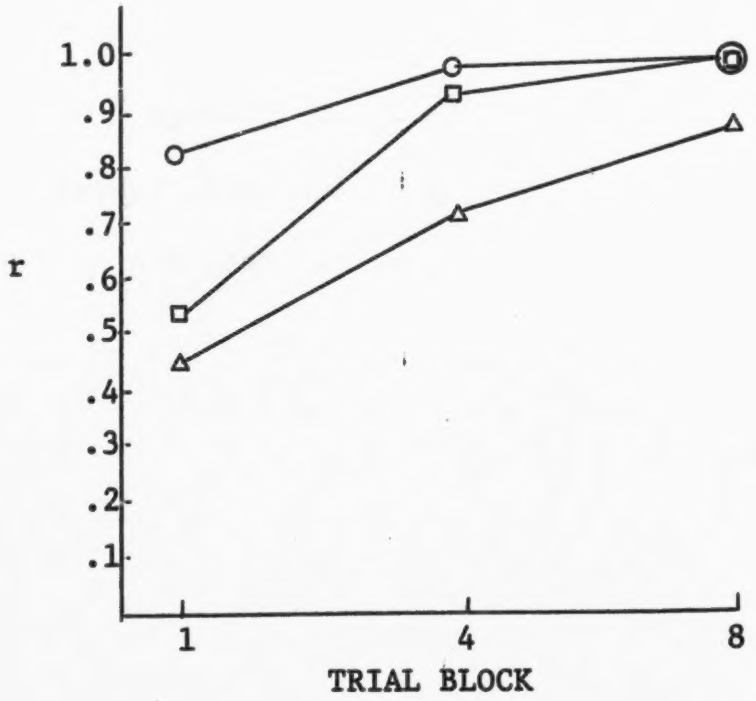


Fig. 46. Correlation r between empirical data and predicted results based upon the G1, P4 Solution.

○——○ College

□——□ Grade School

△——△ Retarded

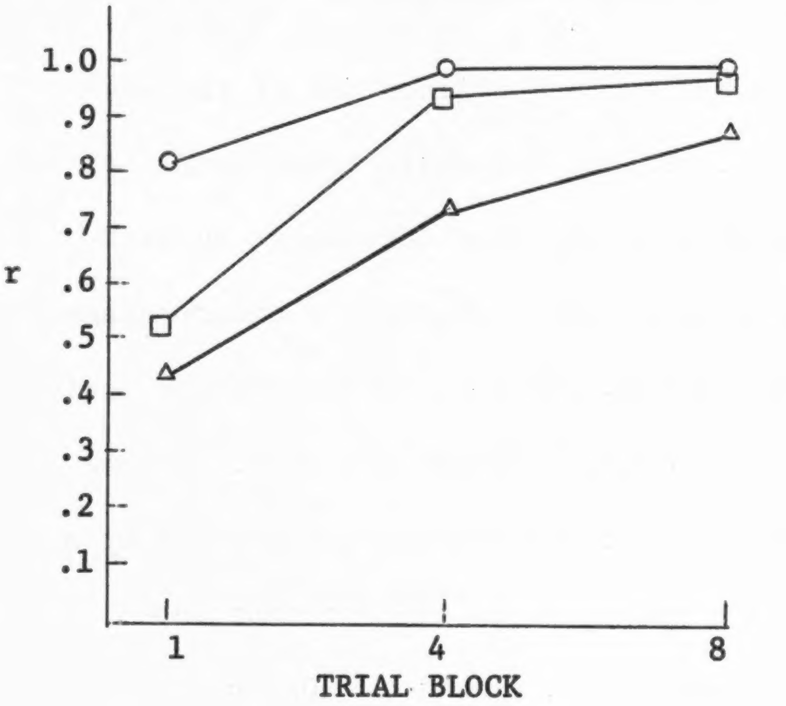


Fig. 47. Correlation r between empirical data and predicted results based upon the G3, P5 Solution.

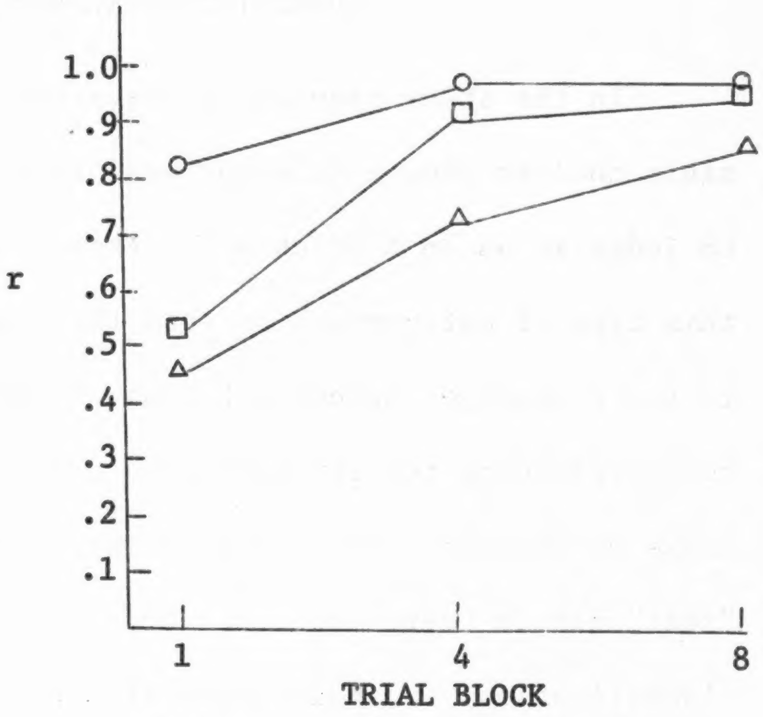


Fig. 48. Correlation r between empirical data and predicted results based upon the G2, P5 Solution.

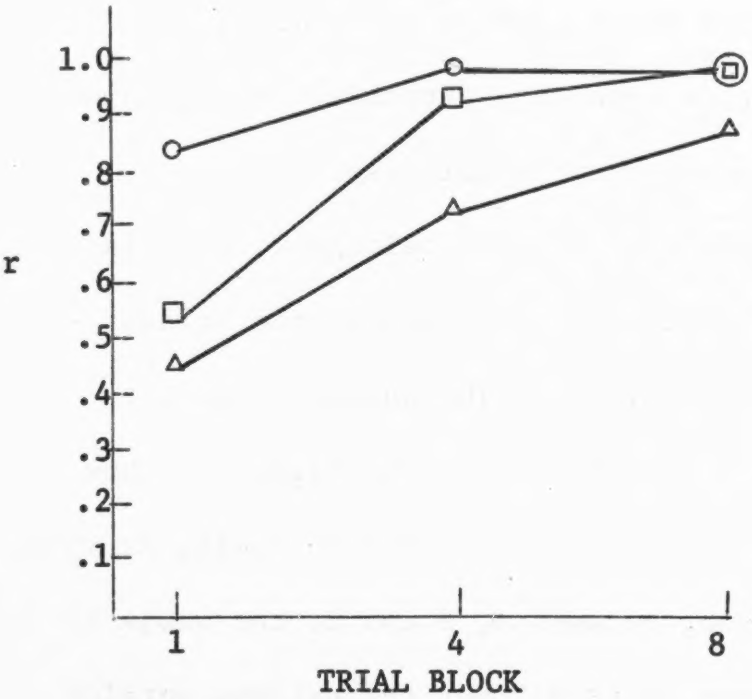


Fig. 49. Correlation r between empirical data and predicted results based upon the G1, P5 Solution.

○———○ College

□———□ Grade School

△———△ Retarded

SECTION IV

QUANTITATIVE RESPONSES TO STIMULUS AGGREGATES

In the study previously described, subjects were allowed one of two possible choices when a stimulus was presented. Either the subject was permitted to judge it as an X or as a Y. Procedurally this was good because it is with this type of categorization that these studies relate. There is a disadvantage to the procedure, however, because binary classification is an insensitive scale for determining the strength of a percept. Judgments seldom are either of one class or another. They tend to vary within each classification. We speak of a "real" man, a "very" cold day or a "typical" book. It is evident that subclassifications are being made within the major classification. Organisms are predisposed to relate classes along those continua that they have in common. One class of things is thought of as being bigger, prettier or softer than the other class. Thus differences between things are seen to be a matter of magnitude rather than of kind. This is a highly useful way of classifying the phenomenal universe. If the tendency were only to discriminate between those attributes that one class has and the other does not possess, the world would consist of isolated, unrelated elements. Organization requires that in some way everything impinge upon everything else. A discontinuous universe is a chaotic universe.

In addition to asking the subject whether a stimulus belongs to one class or another, it is also rational to ask how strongly it belongs to that class. A certain anomaly results from this question, however. The subject does not tend to base his judgment on how typical the stimulus is to the class, but how different it is from other classes. This is illustrated in the following example. If a continuum is divided into three impinging classes A, B and C, the subject will report the central cases of B to be most "B like," but the extreme outside cases of A and C are reported as most "A and C like." Similarly, using two classifications, the extreme cases are regarded as being most representative of their class. Hence, all cases of the two classes, X and Y, can be measured either in terms of how "X like" or how "Y like" they are. To the extent that the stimuli are judged to be unlike the distally extreme cases of Ys, the more "X like" they are perceived to be. The judgment is apparently based upon probability rather than typicality. The statement that someone is "quite a man" is more likely to be in reference to a variant than to a representative case.

An advantage then in requiring the subject to give a quantitative response is that greater sensitivity of measurement is obtained. In these experiments groups are studied rather than individuals, only because it is assumed that in so doing atypical variations are cancelled out. It is the individual rather than the group, however, that is of interest. In the previous study it was assumed, for purposes of analysis, that the proportion of subjects responding in a given way was directly related to how strongly each individual in the group felt about it. This assumption may turn out to be empirically justified, but it cannot be rationally justified without some demonstration. If all of the subjects feel reasonably certain that a stimulus belongs to a particular category, they should give identical results with the situation where they all feel very strongly that it belongs to that category. Hence, the two situations would be judged as equal by the dual-choice method, which in fact they are not.

The desire to obtain a quantitative response is not easy to satisfy. Ordinarily if quantitative responses are given, quantitative knowledge of results are expected. To require the subject to indicate the strength of his belief, but only to give categorical knowledge of results, would be artificial and probably not very successful. At the same time it is apparent that within the general approach of these researches, it is not possible to give quantitative knowledge of results without affecting, in an undesirable manner, the evolution of the perceptual process.

In the present study an attempt was made to overcome these procedural difficulties by having the subject indicate the strength of his belief by making a wager on its correctness.

In an earlier study by Elam (1962), betting procedures were used in experiments. Subjects were required to lay a wager on the accuracy of their judgment. It was assumed that the wager would be proportional to the strength of the judgment and thus the amount wagered would be proportional to the degree of perceptual certainty.

The procedure was only partially successful. It was found that individuals were extremely variant in their betting behavior. Males, as a rule, tended to bet more than did females. Some individuals would always bet the minimum or maximum amount allowable. The data, being highly skewed for a given subject, were, in consequence, no better than categorical discriminations. What was needed was for each individual to use the total range provided. In the present study this was attempted by varying the ratio of how much was won if the categorical response was correct, as well as how much was lost if the response was wrong. If it was seen that an individual was tending to overbet, this was attenuated by decreasing the reward for correct responses. If a tendency was registered in the opposite direction, the ratios were allowed to compensate for this as well. Based upon this individual treatment, it was assumed that the amount bet was an index of the strength of the percept adjusted for individual differences in betting.

METHOD

Subjects

Three groups were used. The first was a normal high school group drawn from the junior and senior classes of the public schools. Two high schools were involved. Both served a wide range of socio-economic levels. The second group was composed of third, fourth and fifth grade students from three Fort Worth public schools. The socio-economic levels for the grade schools were somewhat higher than for the high schools. This probably was advantageous from a control point of view, however since due to drop-outs, the intelligence of classes undergoes some relative increase with the higher grades. The third group was obtained from the Denton School For The Mentally Retarded. These were given the IV classification (Sloan & Birch, 1955) of mental retardation.

The group sizes were 128, 89 and 110 for the high school, grade school and retarded groups respectively.

Procedure

Each child was tested independently using a specially built apparatus. The apparatus consisted of a 35 mm projector, the image of which was focused on a 4" x 4" translucent screen. The subject responded by adjusting a knob which turned a potentiometer. Turning the knob to the right was in effect a judgment that the stimulus was an X. Turning it to the left was a judgment that it was a Y. The distance turned from center determined the amount of the bet. The minimum bet was one cent, while the maximum was ten cents. After selecting the direction and distance of the knob, the subject pressed a push button switch to register his response. At this moment a meter was automatically engaged to show how much the subject has won or lost. To win the subject has to turn the knob in the proper direction. The amount lost was simply a function of how far the knob was turned. The amount won, however, was a function of both how far the knob was turned and the ratio of reinforcement selected by the experimenter from his control panel. All subjects were started on a 1/1 ratio. When their response pattern became skewed the experimenter gradually adjusted his control to correct for the pattern. By this procedure the subject was induced to respond in a more selective and distributive manner using the entire available range of betting possibilities.

Four hundred pictures were shown and an equivalent number of responses obtained from each subject. The pictures contained four relevant cues. Again the image of the girl was shown with the position of the head, arms and legs varying through 20 values. In addition to these cues a horizontal bar was seen above the girl's head. The length of this bar also varied through 20 positions.

In the course of the 400 trials each of the 20 variations of the 4 cues was shown 20 times. The frequency of occurrence as related to the X and Y categories is shown in Figures 50, 51, 52 and 53. The association of cue variations was random except for the restriction imposed by these distributions.

It has been previously established that the 20 variations of each cue were linear in their subjective displacement from one another. For purposes of analysis the stimulus variations can consequently be regarded as equi-distant from one another on a perceptual scale.

RESULTS

The control of reward using the procedures described above generally exerted a salutary effect upon the scaling of response strength. In most cases the subjects used the entire available range of betting possibilities. In other cases the procedure, while controlling the employment of either maximum or minimum wagers, tended to produce an approximately equal occurrence of each. This in effect produced a four rather than the twenty unit scale desired. The procedure was generally more effective with high school students than with the grade school. It is unfortunately the case that only very few of the retarded seemed to be

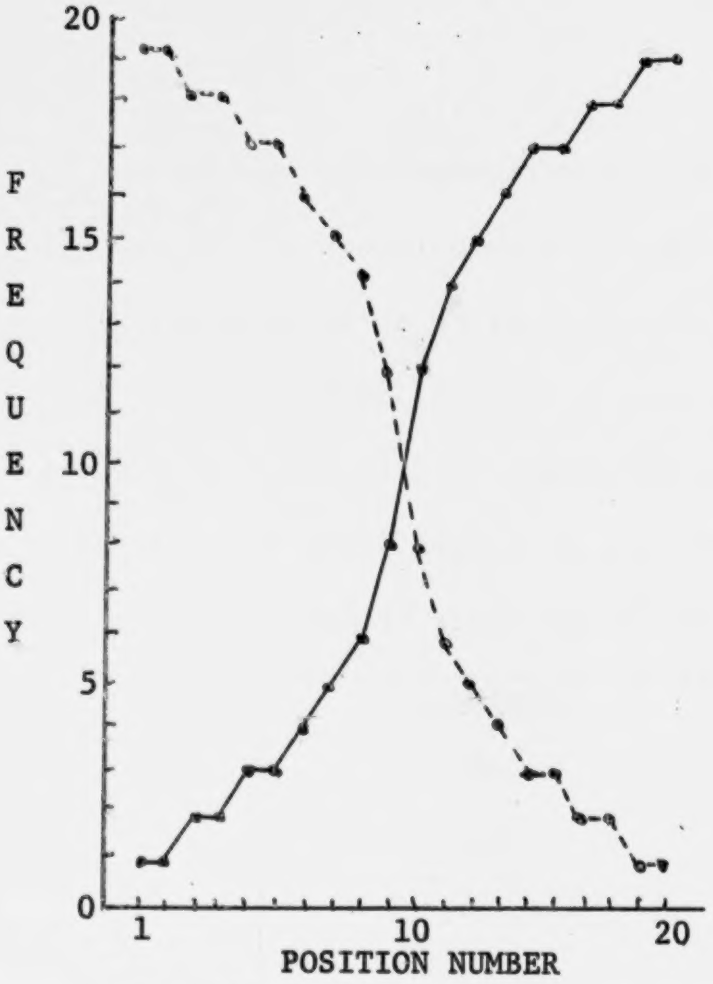


Fig. 50. Distribution of cue variations for head position of the X and the Y stimulus population.

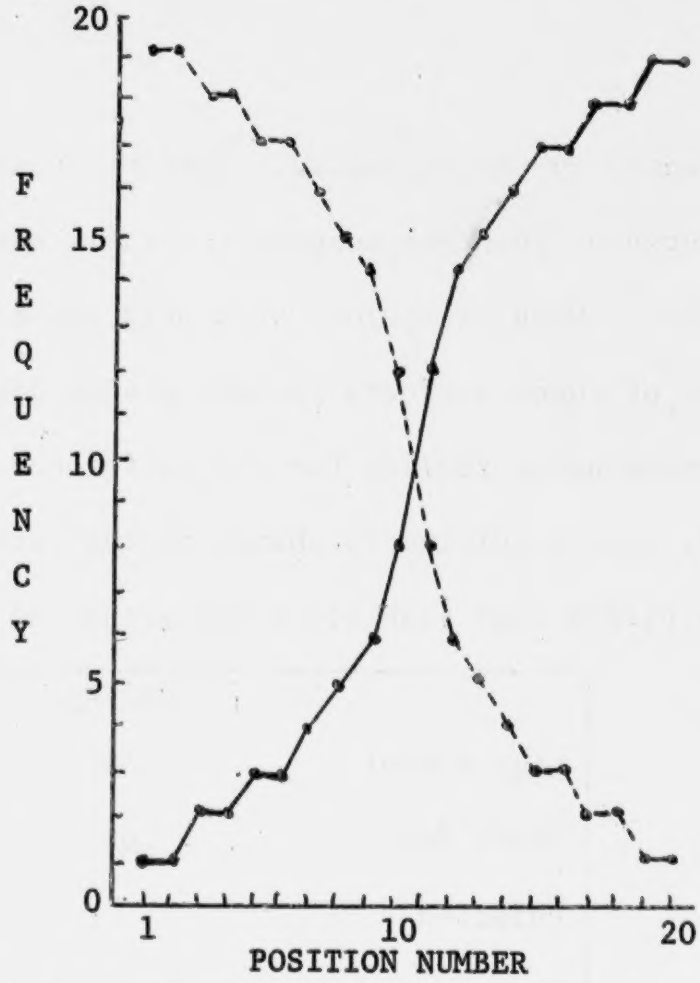


Fig. 51. Distribution of cue variations for arm position of the X and the Y stimulus population.

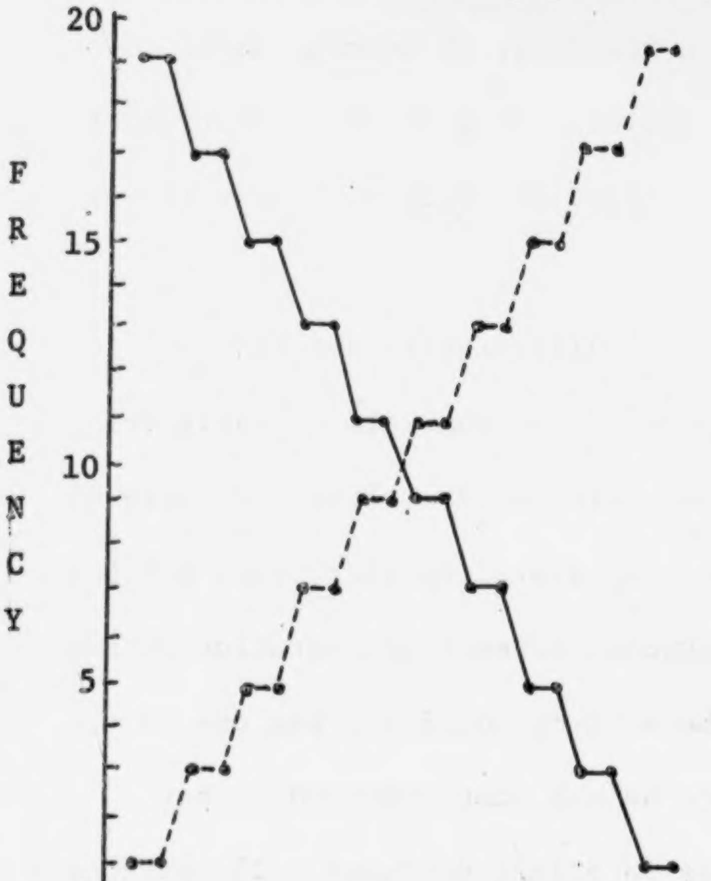


Fig. 52. Distribution of cue variations for leg position of the X and the Y stimulus population.

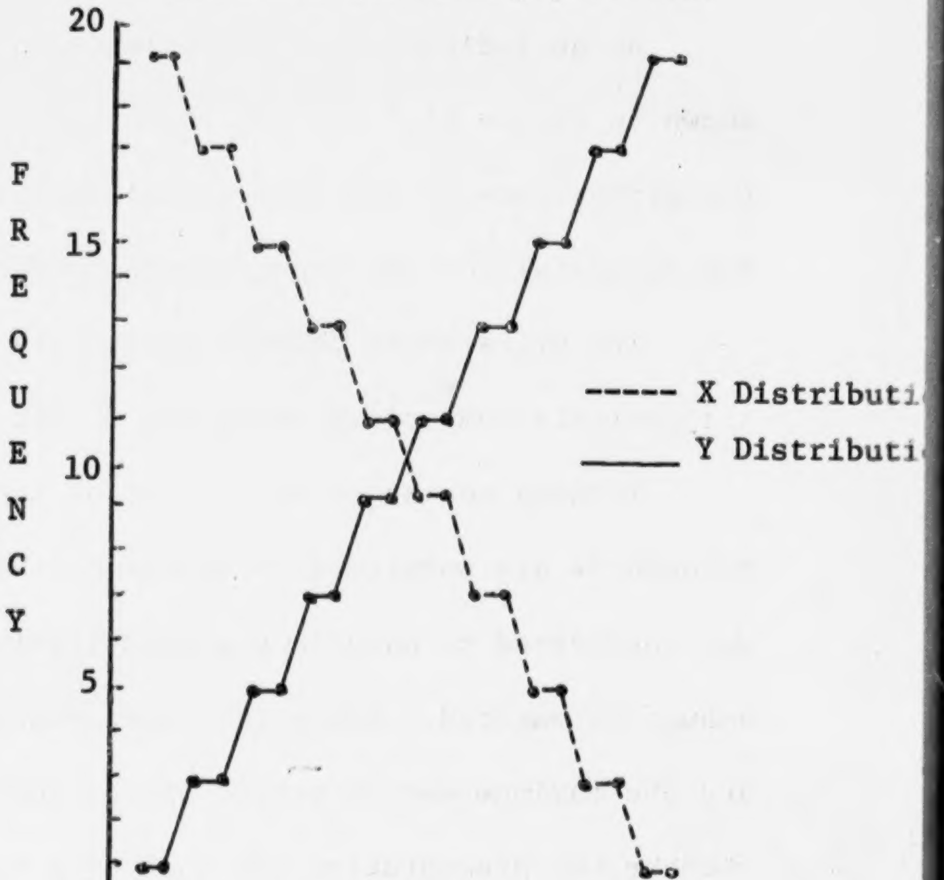


Fig. 53. Distribution of cue variations for bar position of the X and the Y stimulus population.

affected by the procedure. Most of these subjects gave sterotyped responses throughout the test despite the ratio changes and the admonitions of the experimenter. When variations were obtained they were usually of a random character. Most of these subjects picked up some distinction between X and Y stimuli. All of them had a feeling for the difference between winning and losing, but few, if any, were sensitive to change in the ratio of wins to losses. The mean values of the ratios that stabilized the groups is shown in the table below:

	Males	Females
High School	.45	.60
Grade School	.60	.68
Retarded	1.30	

The mean ratio of the amount won to amount lost that tended to produce a use of the total available scale.

As an indication of performance the mean frequency of reinforcement is shown in Figure 54. For the three groups of subjects as a function of trial block, the performance of the high school group is regarded as being very near the maximum potential for any known logical process.

The differences between groups are statistically significant (P < 05) for all possible comparison using the t test preceded by an analysis of variance.

Turning now to an evaluation of the model introduced earlier. Figures 55 through 94 are submitted in reference thereof. As stated earlier, each subject was considered to have made a quantitative response to each presentation by the amount he wagered. Since the least amount the subject could bet was one unit and the maximum amount was 10 units, and since he was also required to bet whether the presentation was an X or a Y, this in effect produced a 20 unit scale of Xness. The data were converted to this scale. If the subject bet 10 units

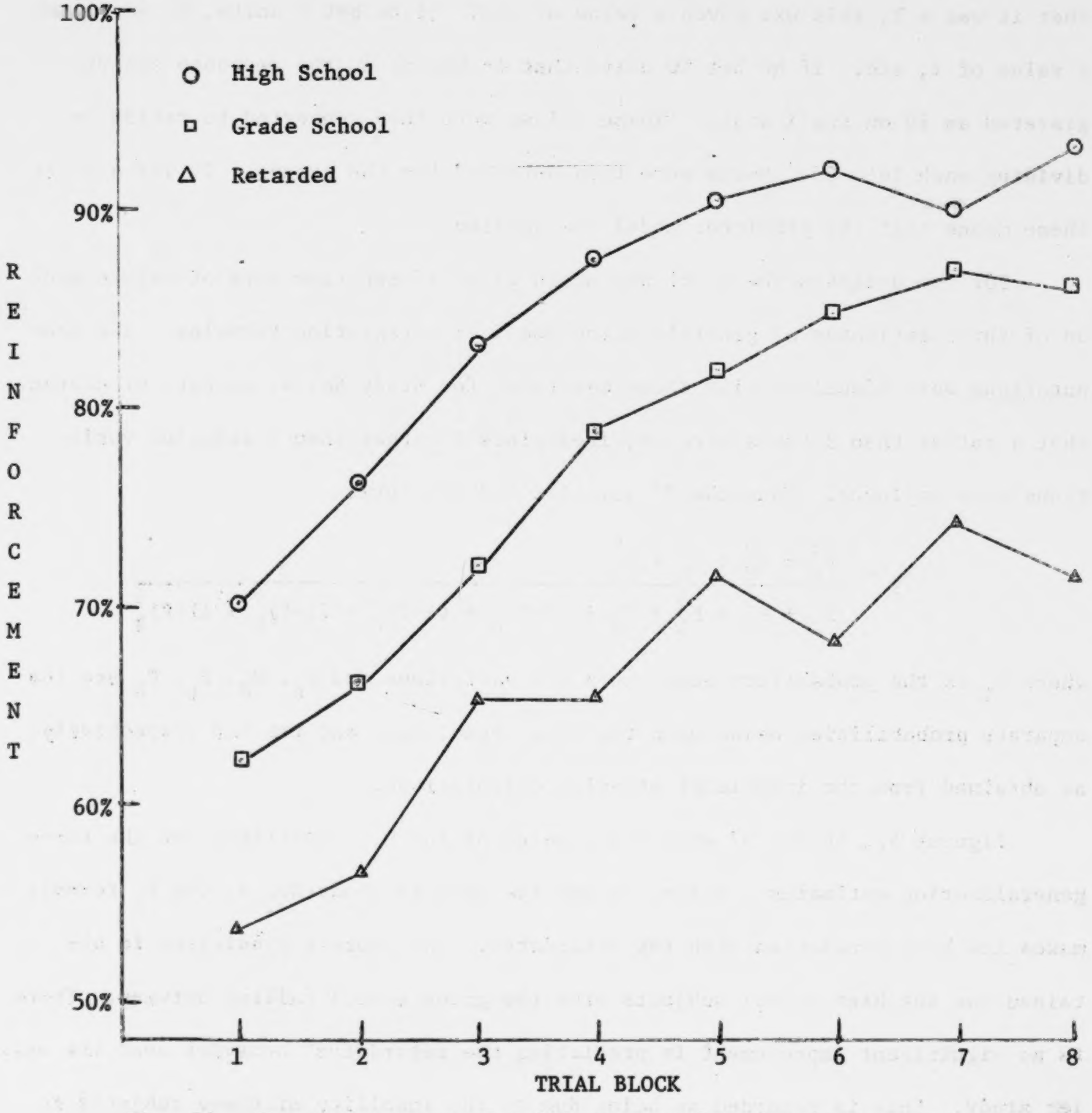


Fig. 54. Mean percentage of reinforcement for the three groups as a function of trial block. Each block consists of 50 trials.

that it was a Y, this was given a value of one. If he bet 9 units, it was given a value of 2, etc. If he bet 10 units that it was an X, the response was registered as 20 on the X scale. These values were then converted to ratios by dividing each into 20. Means were then obtained for the groups. It was against these means that the predictor model was applied.

For the analysis the model was again given 15 separate sets of values made up of three estimates of generalization and five integration formulas. The computations were identical with those described for Study No. 1, except, of course, that 4 rather than 3 terms were required since 4 rather than 3 stimulus variations were employed. Thus the P^5 solution had the form:

$$P_T = \frac{P_A^5 + P_H^5 + P_L^5 + P_B^5}{P_A^5 + P_H^5 + P_L^5 + P_B^5 + (1-P)_A^5 + (1-P)_H^5 + (1-P)_L^5 + (1-P)_B^5}$$

where P_T is the probability based upon all variations and P_A, P_H, P_L, P_B are the separate probabilities based upon the arms, head, legs and the bar respectively, as obtained from the individual stimulus calculations.

Figures 55, 56 and 57 show the results of the P_1 predictions for the three generalization estimates. Again, as was the case in Study No. 1, the P_1 formula makes its best prediction with the retardates. The poorest prediction is obtained for the high school subjects with the grade school falling between. There is no significant improvement in predicting the retardates' behavior over the earlier study. This is regarded as being due to the inability of these subjects to cope with the concept of wagering.

The curve for these subjects is, however, flatter than before, which suggests that the model has become more stable with the use of such quantitative data as were obtained.

The predictors for the grade school and high school students became progressively erroneous as the analysis proceeded, again indicating the inadequacy of this description for normal behavior.

In Figures 58, 59 and 60, which were obtained from the P_2 formula, we immediately see the shift in the groups. The grade school subjects are now the best predicted while the retarded have become the least predictable.

Figures 61, 62 and 63 show a continuation of the trend, as do Figures 64, 65 and 66. Figure 66 shows that the high school students are highly predictable using the P_4 formula. The fact that this curve is not flat indicates that there is some systematic variance associated with trial block that has not been accounted for in the analysis. The experimenter is not certain as to the nature of this factor, although it can be suspected that it is due to the discontinuities of learning. This is to say that it can be attributed to the possibility that the subjects consciously or unconsciously responded selectively to the various aspects of the stimulus configuration. Some loss in predictability was being obtained because of the impossibility in these procedures of determining exactly what combination of stimuli the individual subject was attending to. As the testing proceeded the subject probably began to attend to all relevant cues. The model, of course, assumed that this had been going on all along.

Figures 67, 68 and 69 seem to indicate that the model has passed through the point of best prediction. All of the prediction error curves are higher than was the case with Figures 61, 62 and 63.

Figures 70 through 78 display the data in a different context. From these it is evident that the best stimulus synthesis formula for the retarded is P_1 (see Figures 72, 75 and 78), while P_3 is most descriptive of the grade school students (see Figures 71, 74 and 77), and P_4 is the best for the high school group (see Figures 70, 73 and 76).

Comparison of the three generalization estimates is obtained from Figures 79 through 94. Here the differences are small, but generally speaking, the G_1 estimate is best in predicting high school performance, while G_2 and G_3 are best for grade school and the retarded respectively.

DISCUSSION

These results correspond very closely to those of Study No. 1, indicating that the model is equally good for four cues as for three. It is also evident that some advantage is gained in obtaining quantitative responses using the wagering technique.

Again it is evident that the retarded do not give as much emphasis to the extremely low and high probability values of a stimulus as do the normal. In addition, it can be seen that the effects of reinforcement and non-reinforcement in a stimulus value tend to be transmitted more readily to adjacent stimuli than is the case with normals.

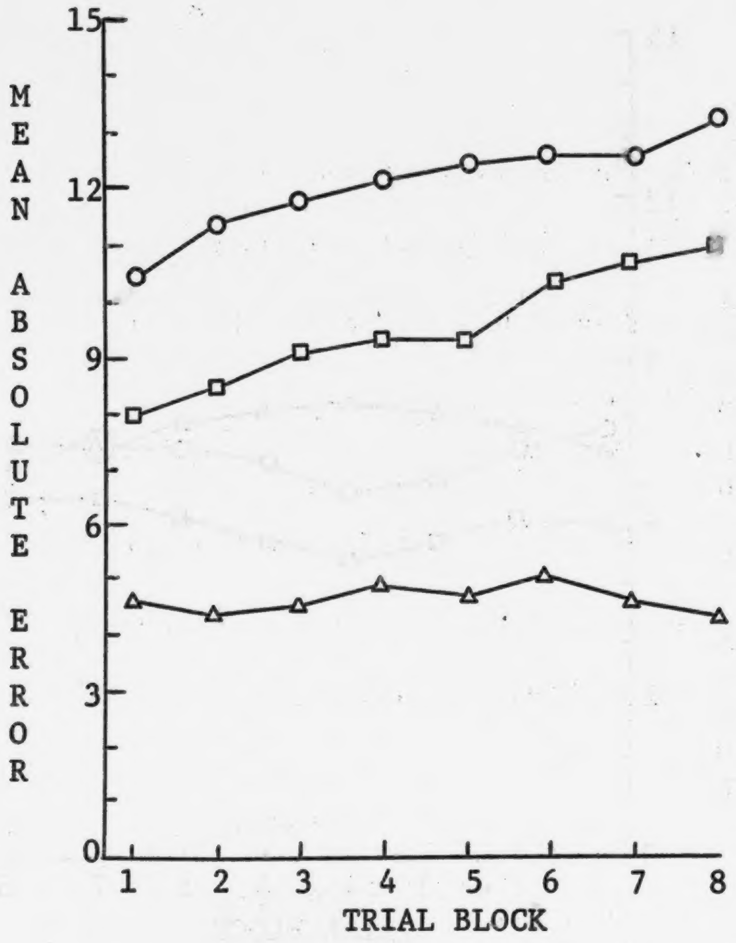


Fig. 55. Mean absolute error obtained in predicting the empirical results from the G3, P1 Solution.

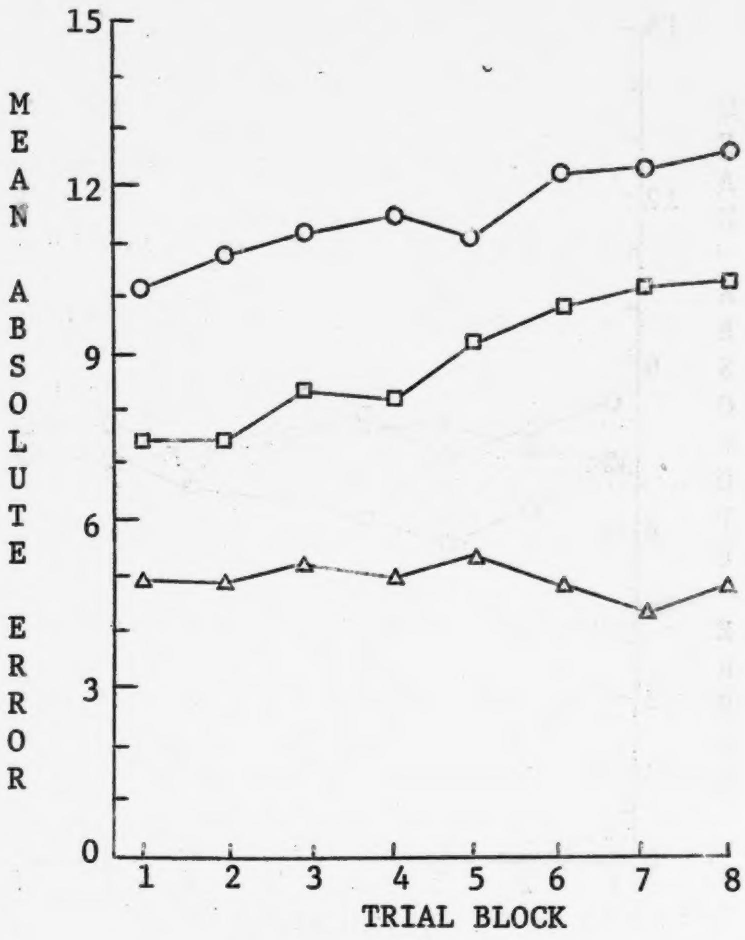


Fig. 56. Mean absolute error obtained in predicting the empirical results from the G2, P1 Solution.

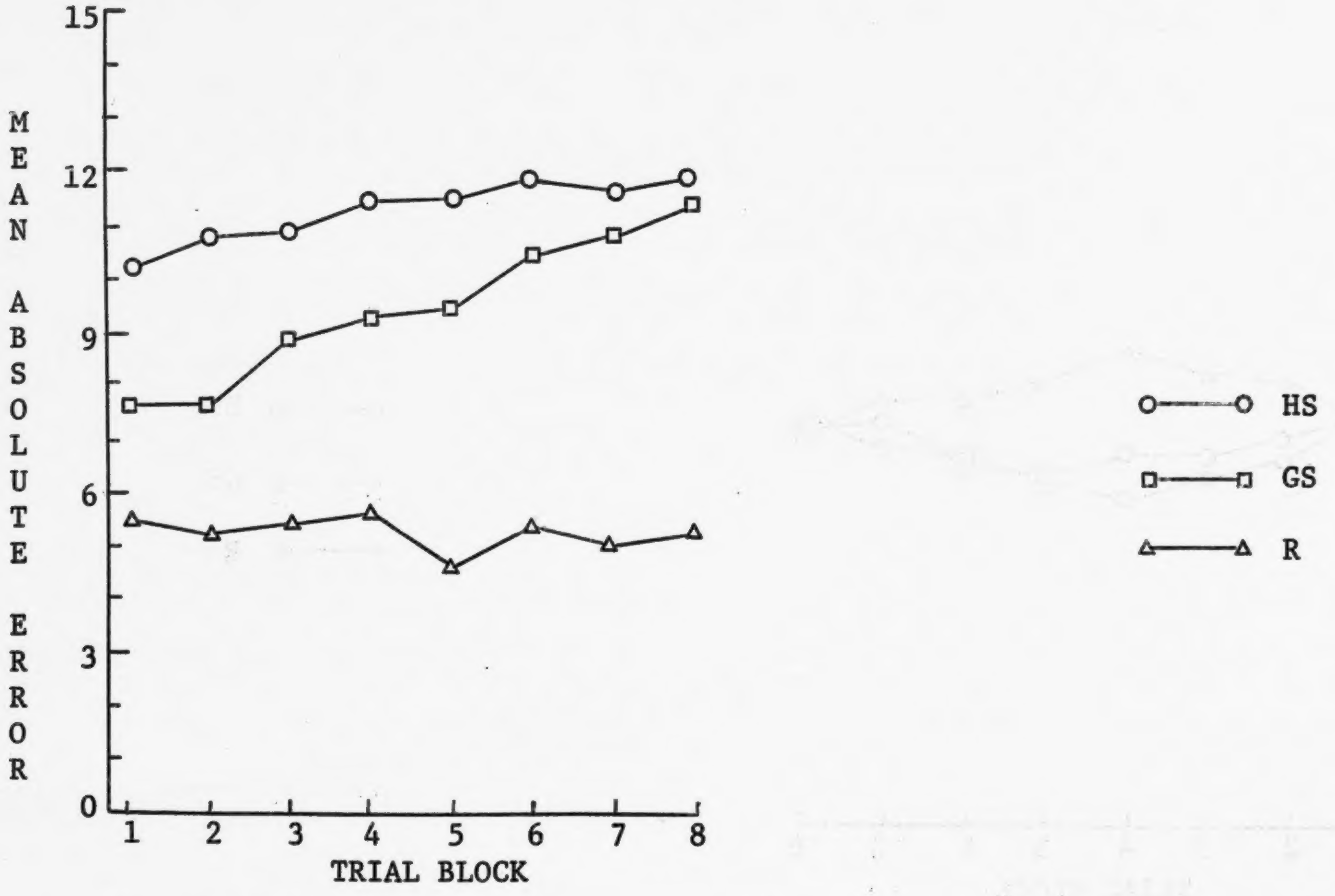


Fig. 57. Mean absolute error obtained in predicting the empirical results from the G1, P1 Solution.

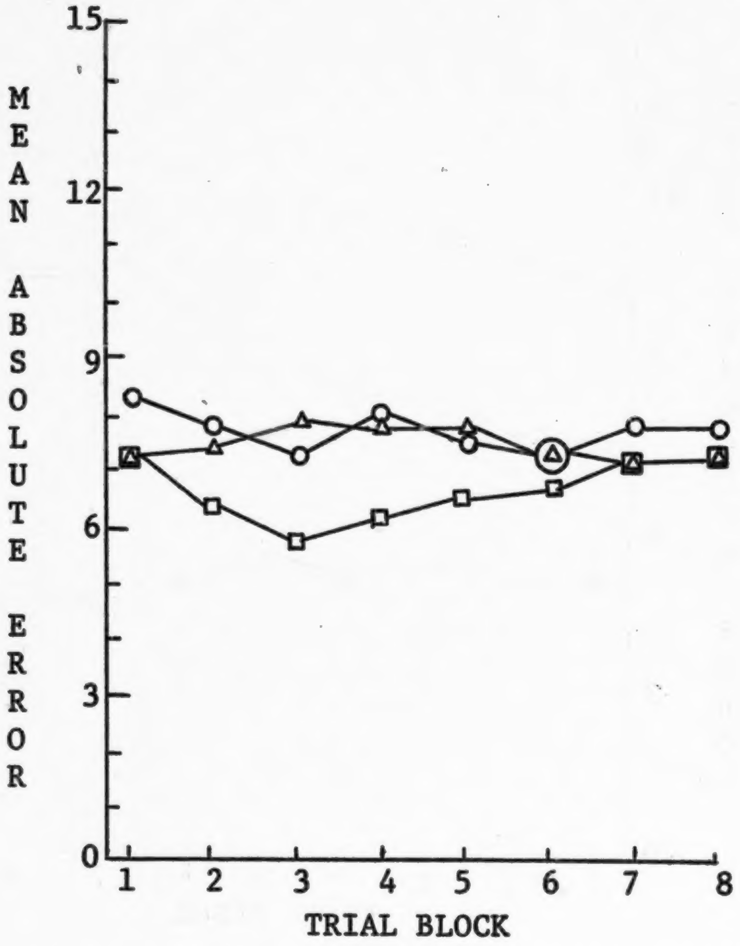


Fig. 58. Mean absolute error obtained in predicting the empirical results from the G3, P2 Solution.

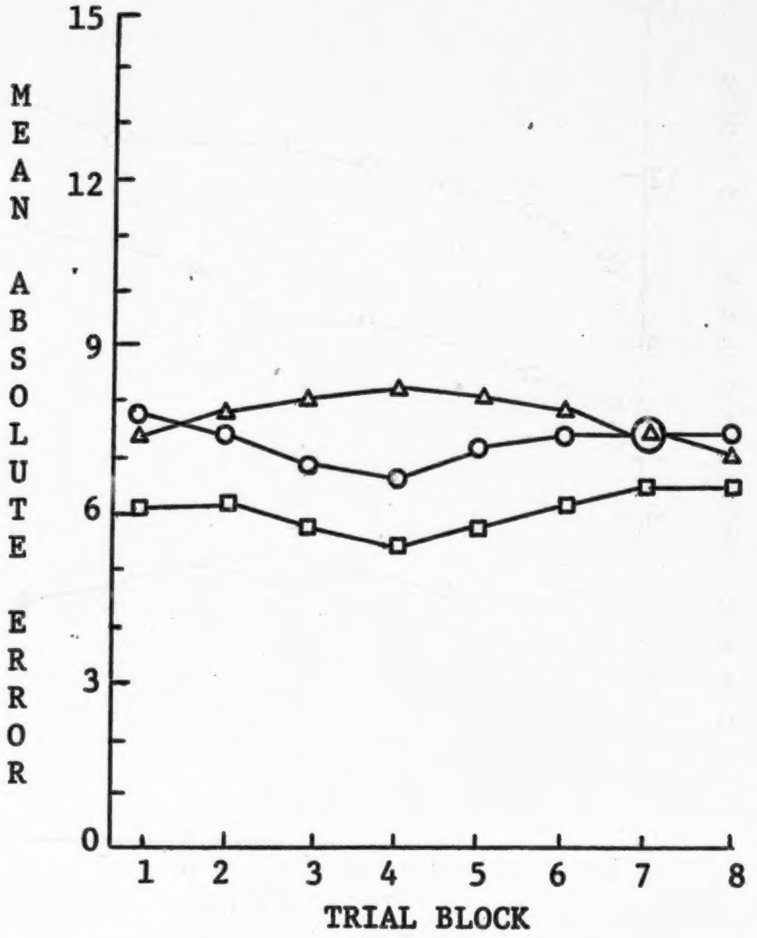


Fig. 59. Mean absolute error obtained in predicting the empirical results from the G2, P2 Solution.

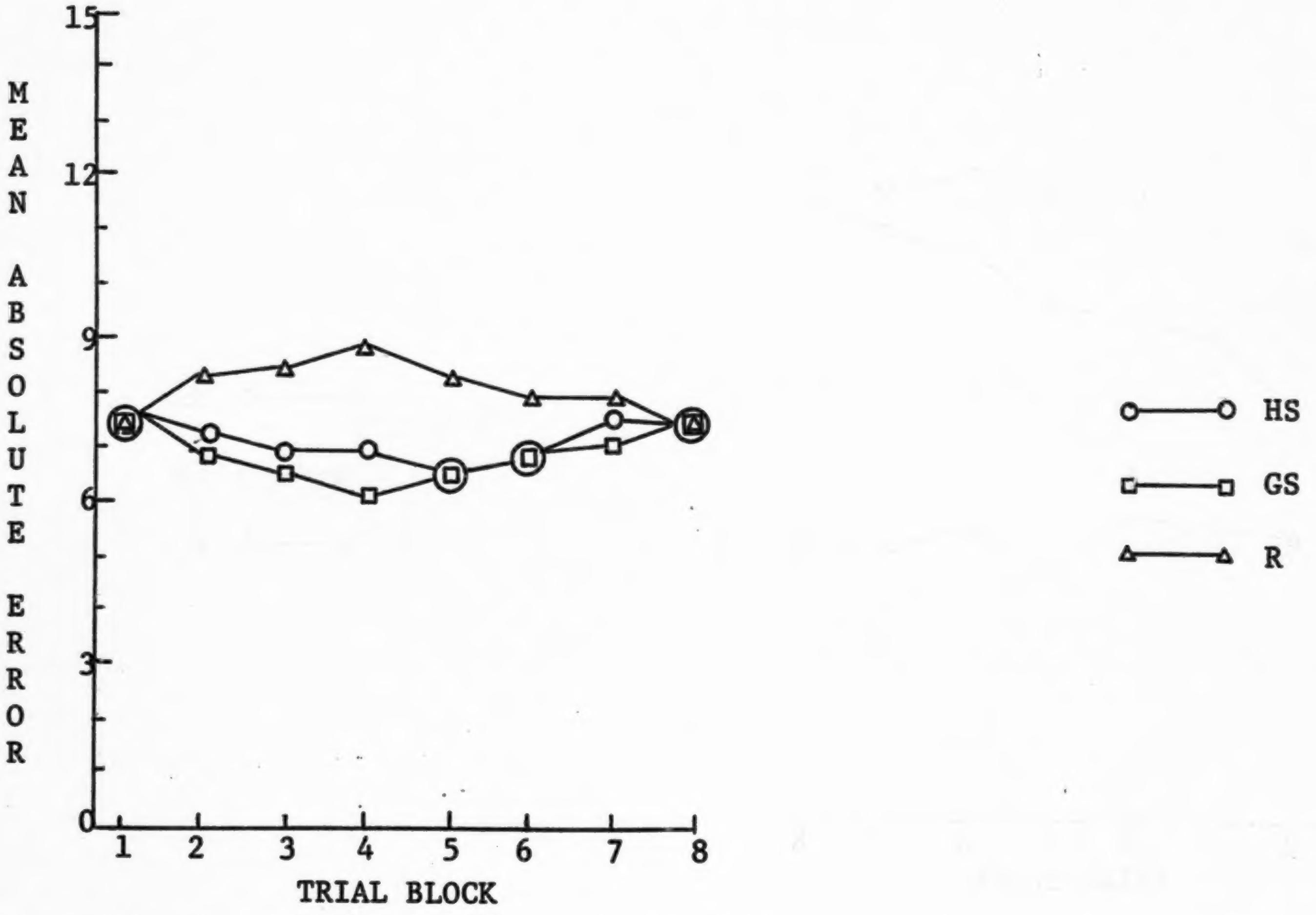


Fig. 60. Mean absolute error obtained in predicting the empirical results from the G1, P2 Solution.

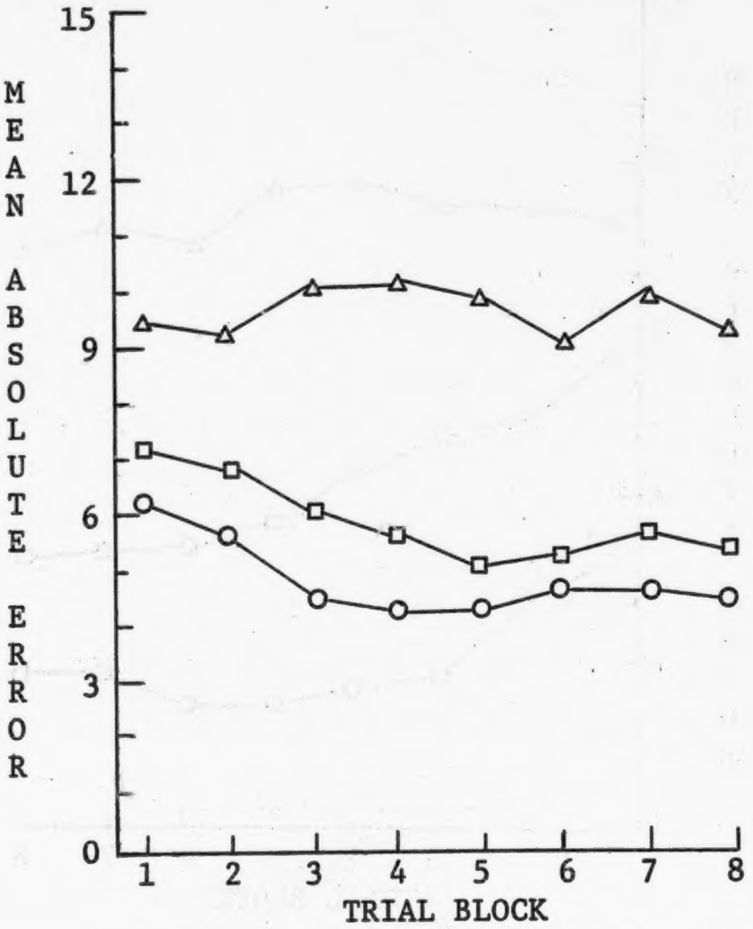


Fig. 61. Mean absolute error obtained in predicting the empirical results from the G3, P3 Solution.

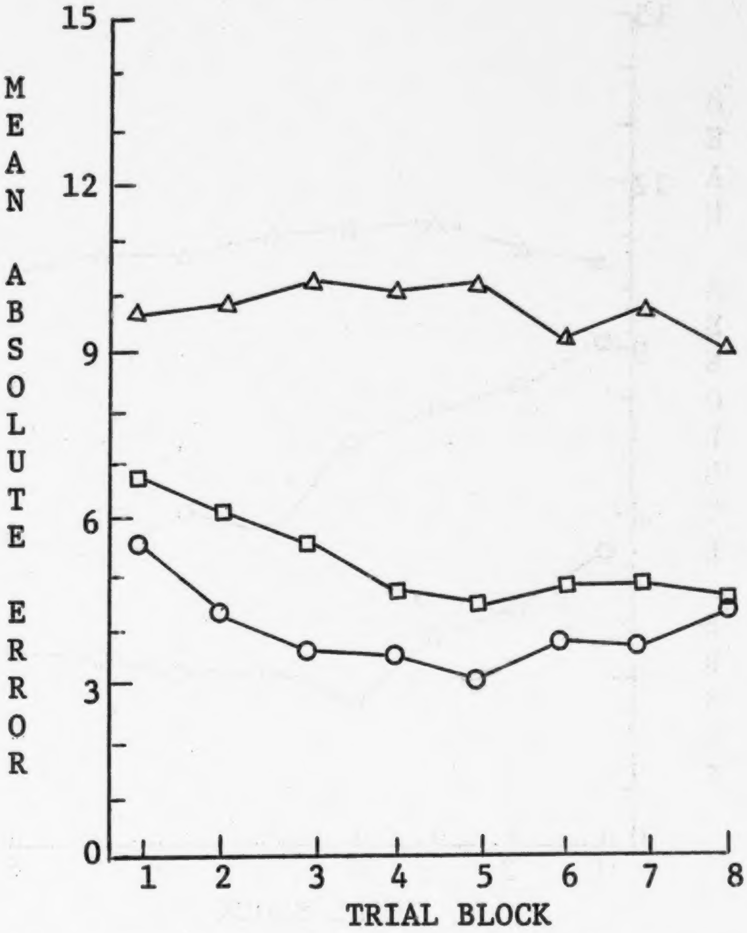


Fig. 62. Mean absolute error obtained in predicting the empirical results from the G2, P3 Solution.

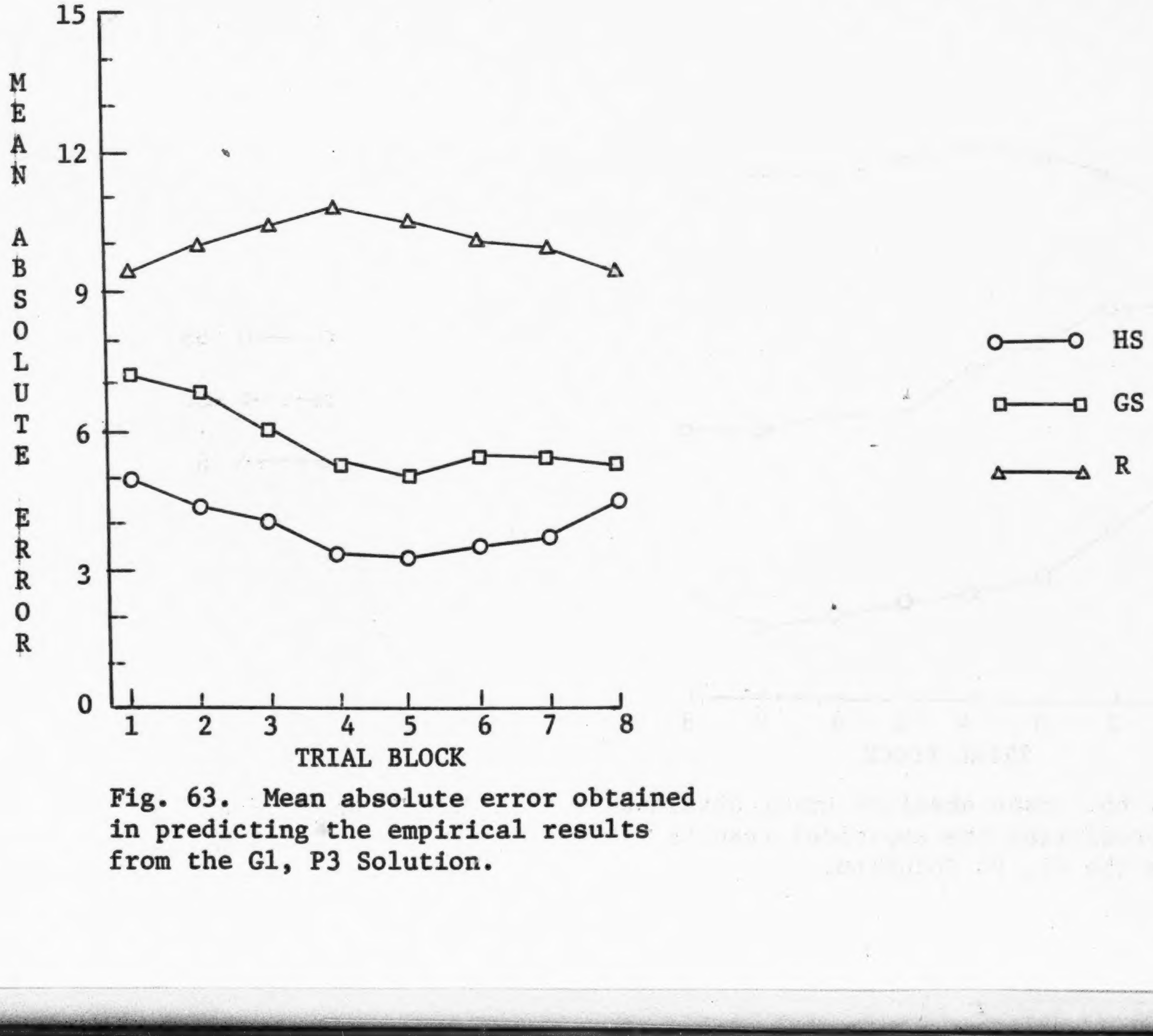


Fig. 63. Mean absolute error obtained in predicting the empirical results from the G1, P3 Solution.

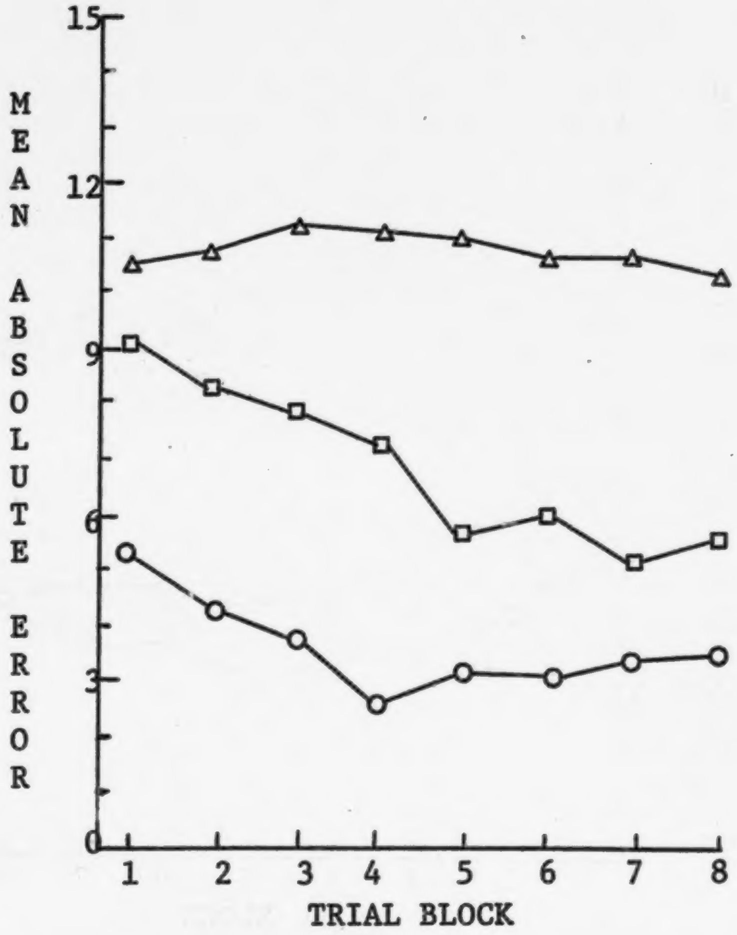


Fig. 64. Mean absolute error obtained in predicting the empirical results from the G3, P4 Solution.

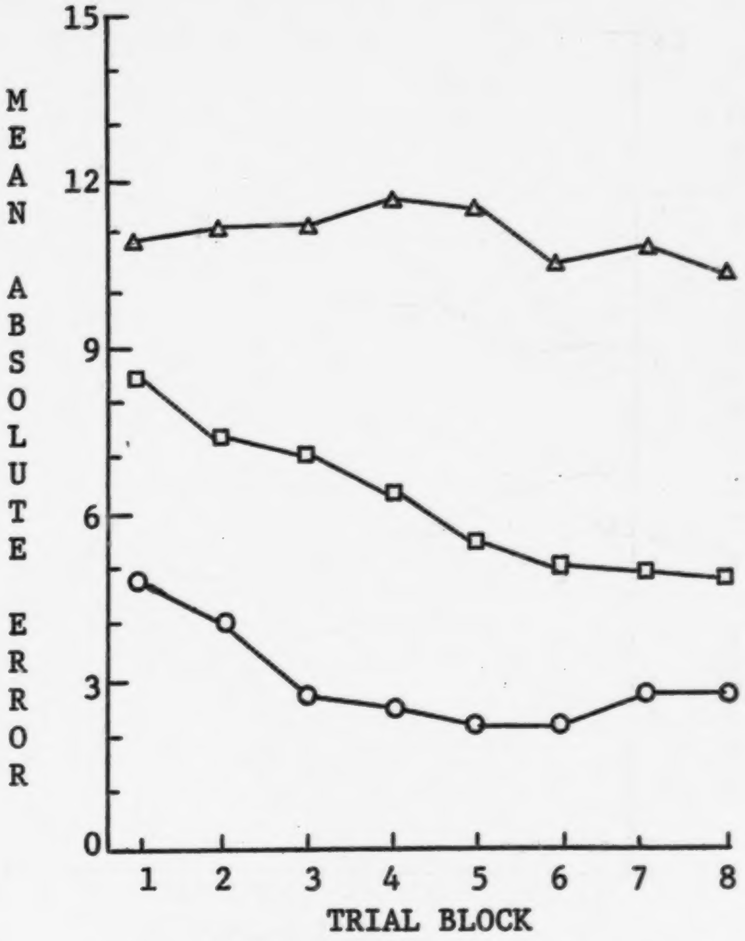


Fig. 65. Mean absolute error obtained in predicting the empirical results from the G2, P4 Solution.

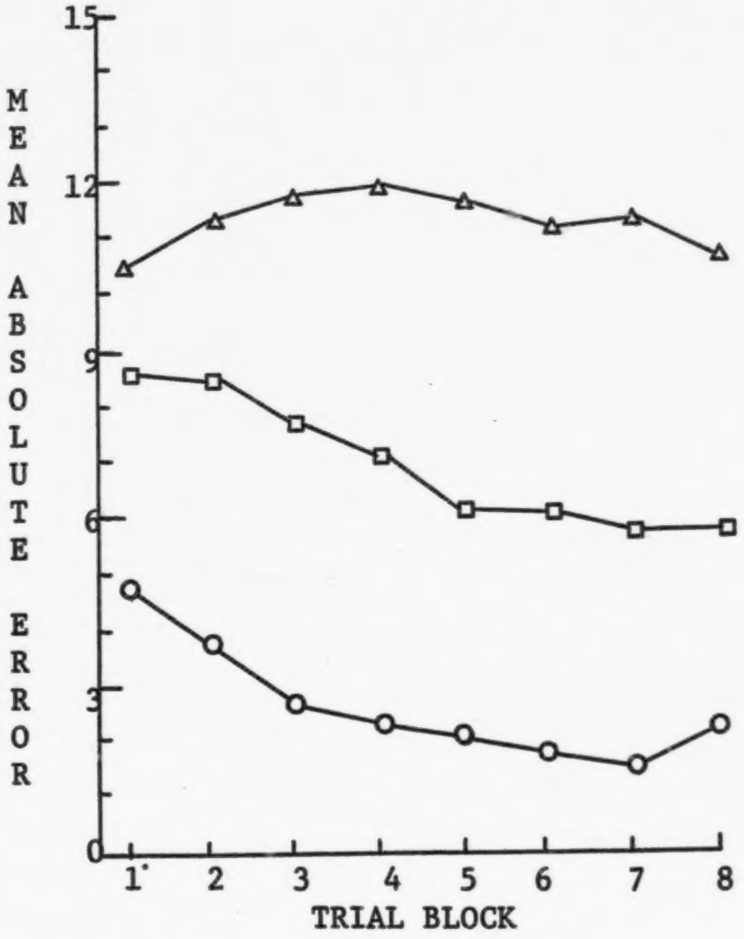
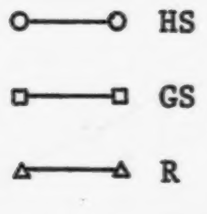


Fig. 66. Mean absolute error obtained in predicting the empirical results from the G1, P4 Solution.



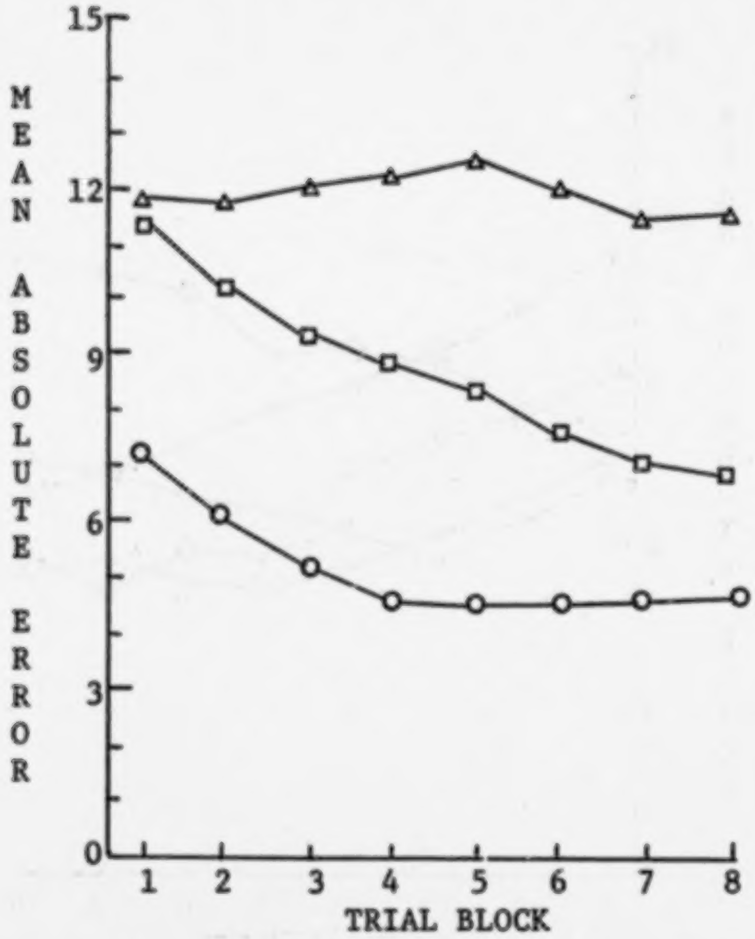


Fig. 67. Mean absolute error obtained in predicting the empirical results from the G3, P5 Solution.

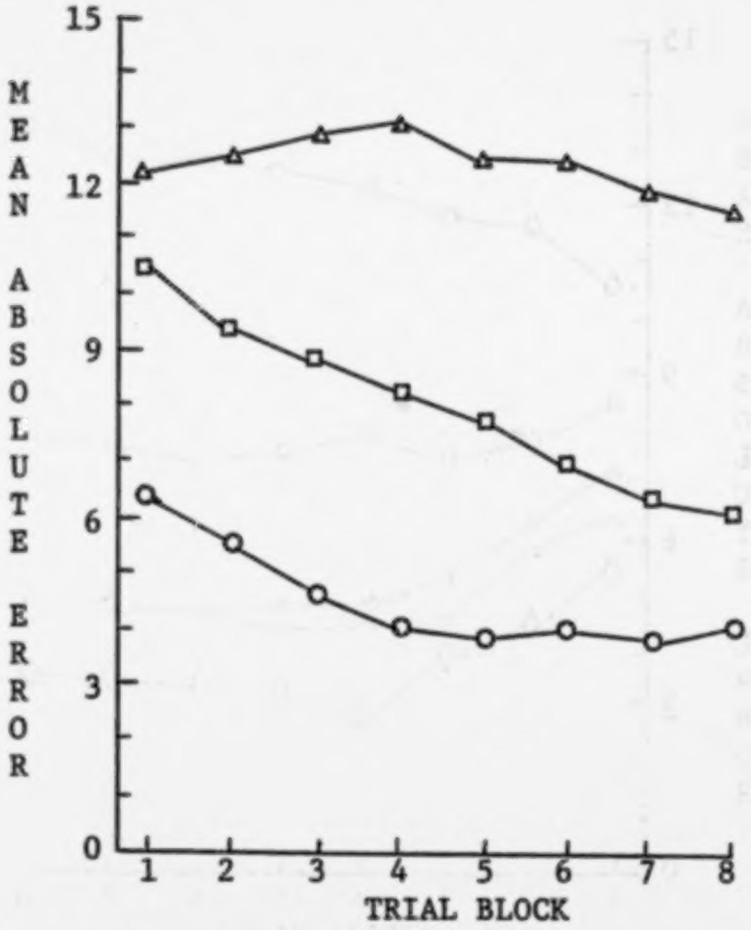


Fig. 68. Mean absolute error obtained in predicting the empirical results from the G2, P5 Solution.

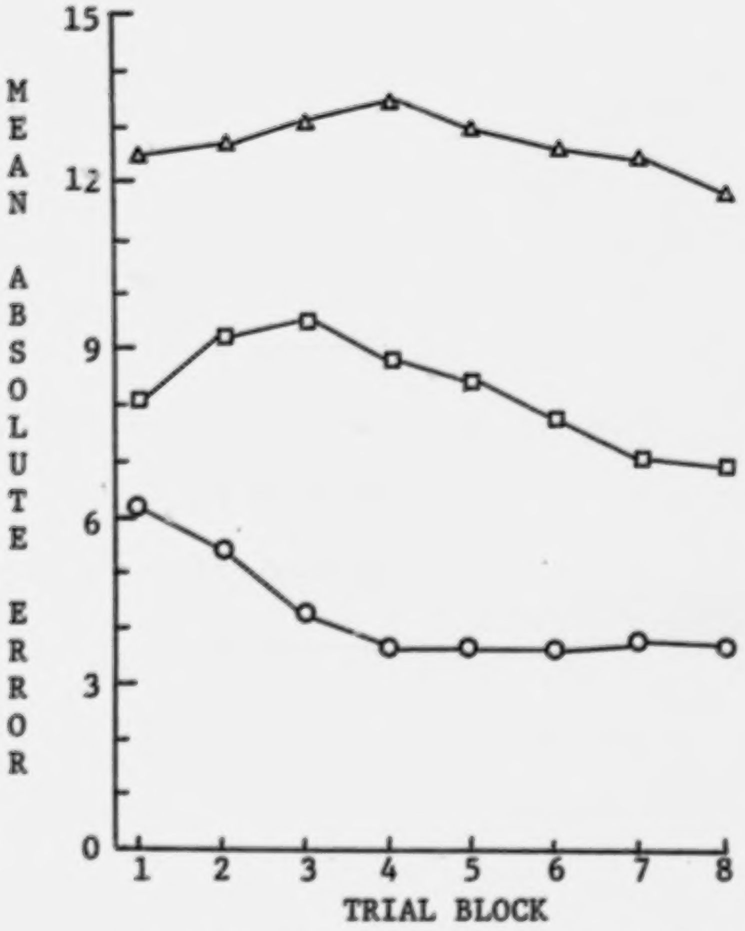
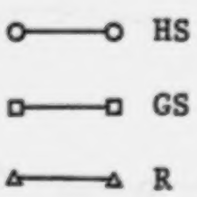


Fig. 69. Mean absolute error obtained in predicting the empirical results from the G1, P5 Solution.



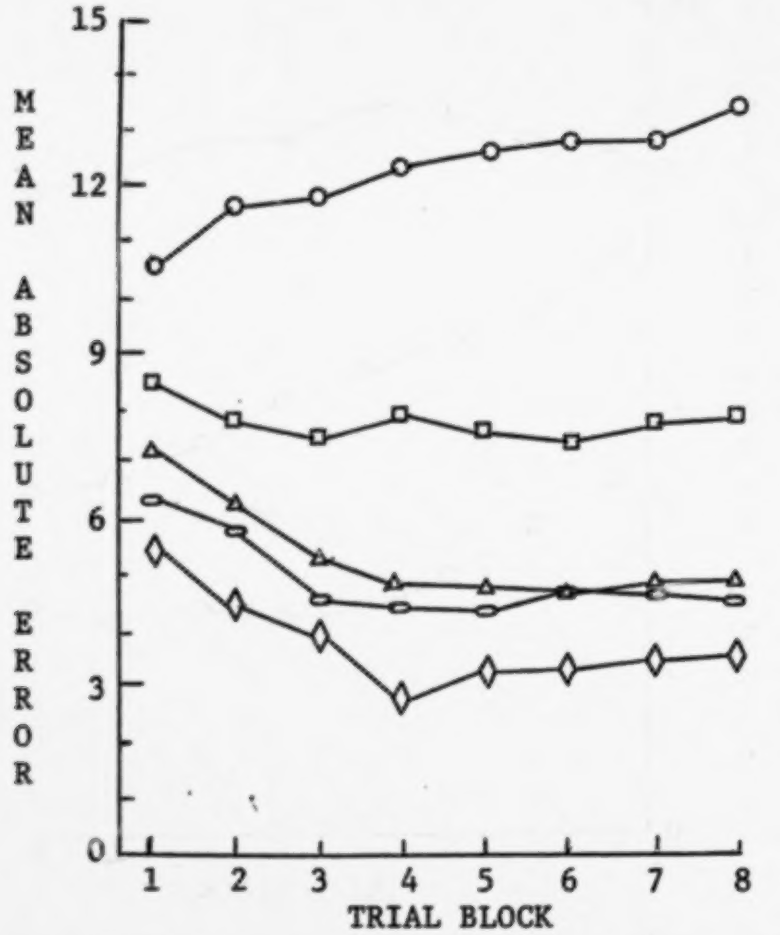


Fig. 70. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). High School Group. G1 formula.

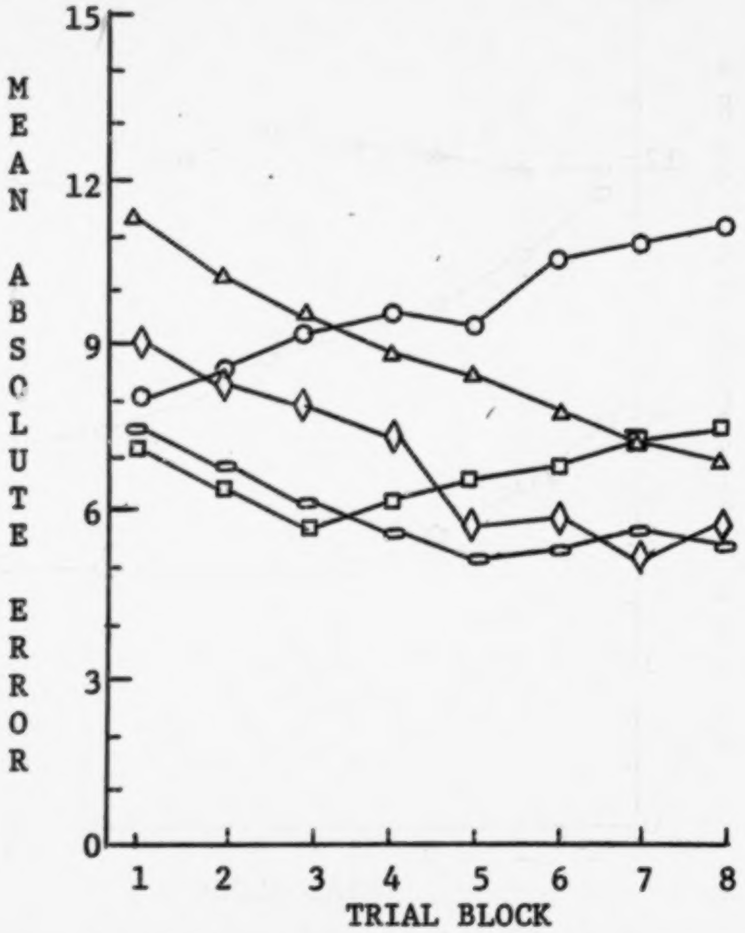


Fig. 71. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Grade School Group. G1 formula.

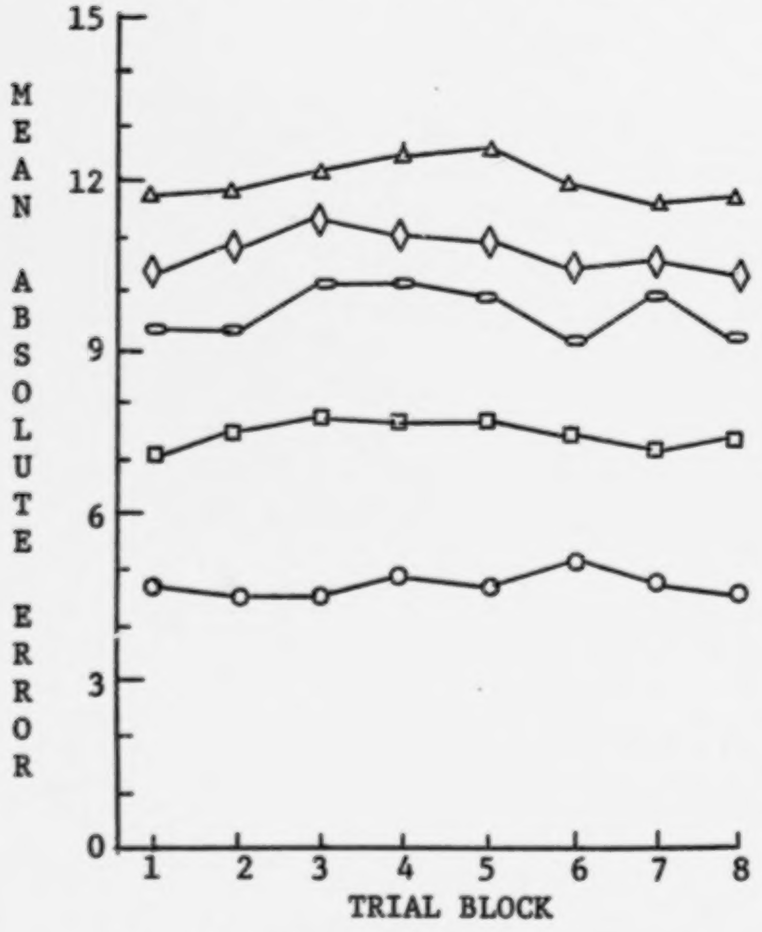
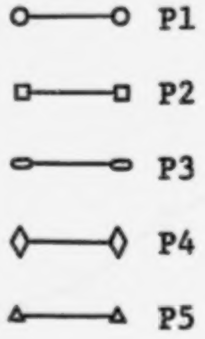


Fig. 72. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Retarded Group. G1 formula.



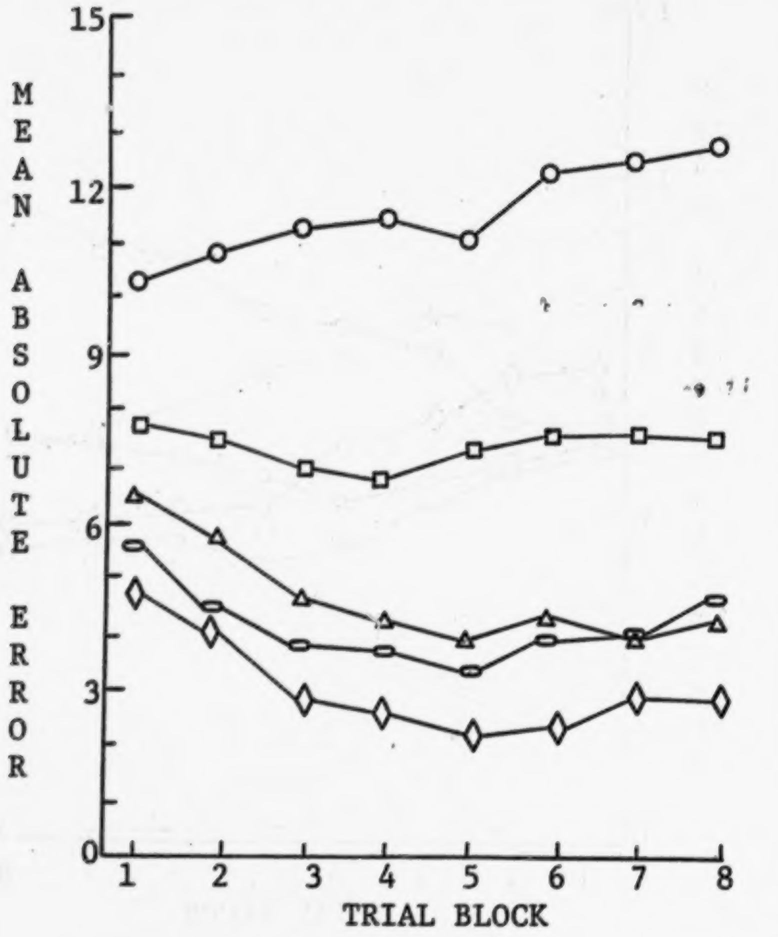


Fig. 73. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). High School Group. G2 formula.

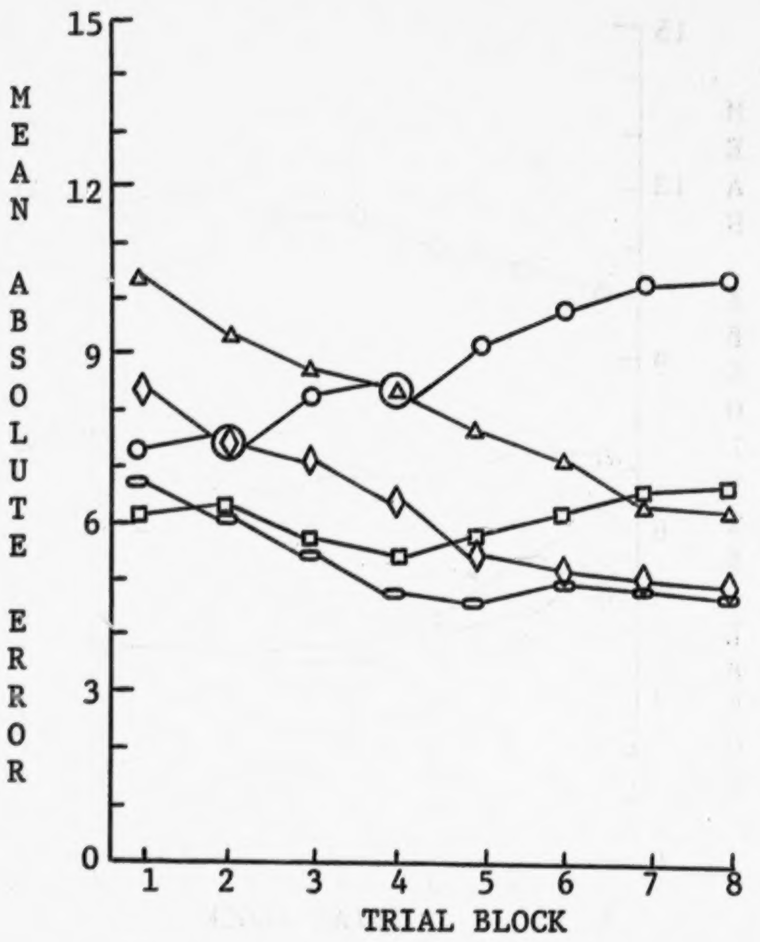


Fig. 74. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Grade School Group. G2 formula.

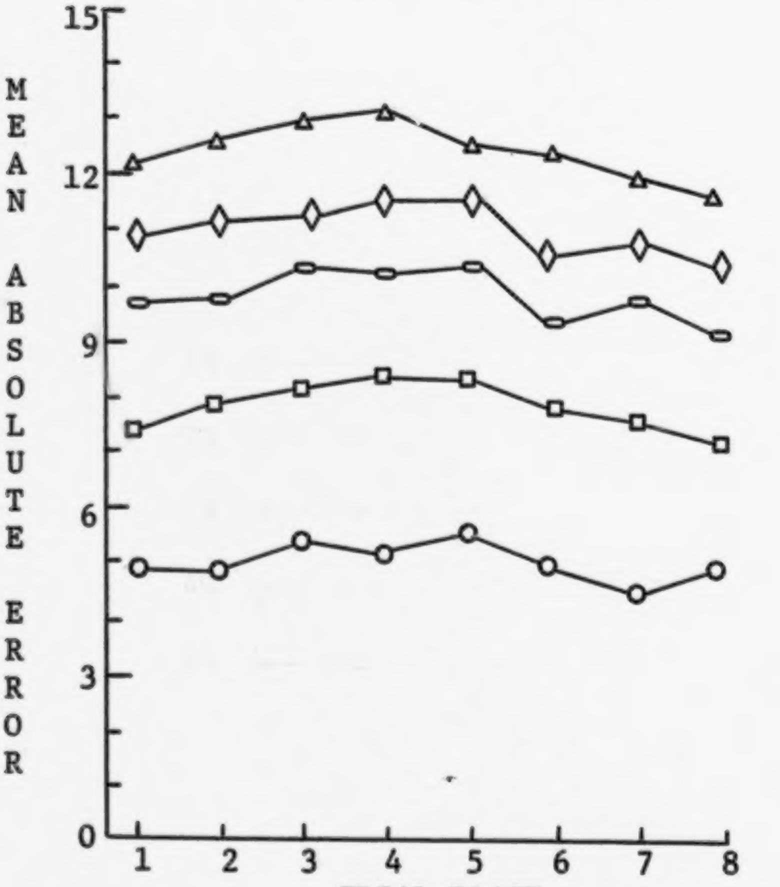
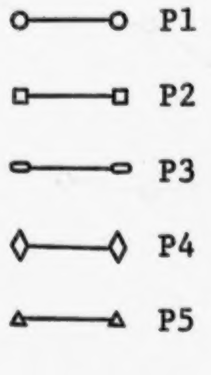


Fig. 75. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Retarded Group. G2 formula.



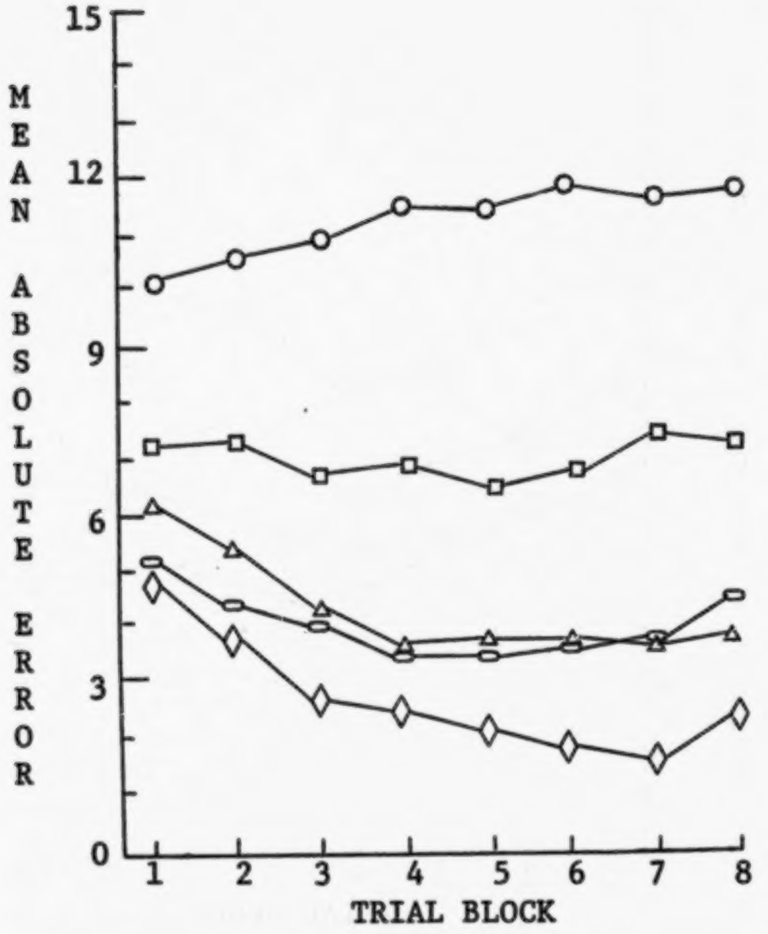


Fig. 76. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). High School Group. G3 formula.

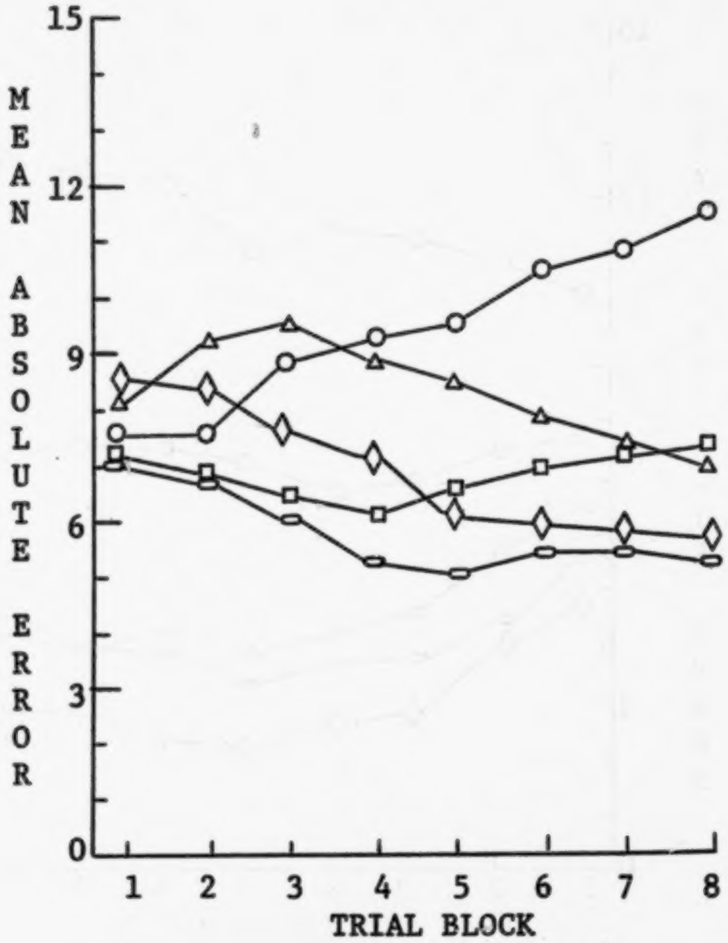


Fig. 77. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Grade School Group. G3 formula.

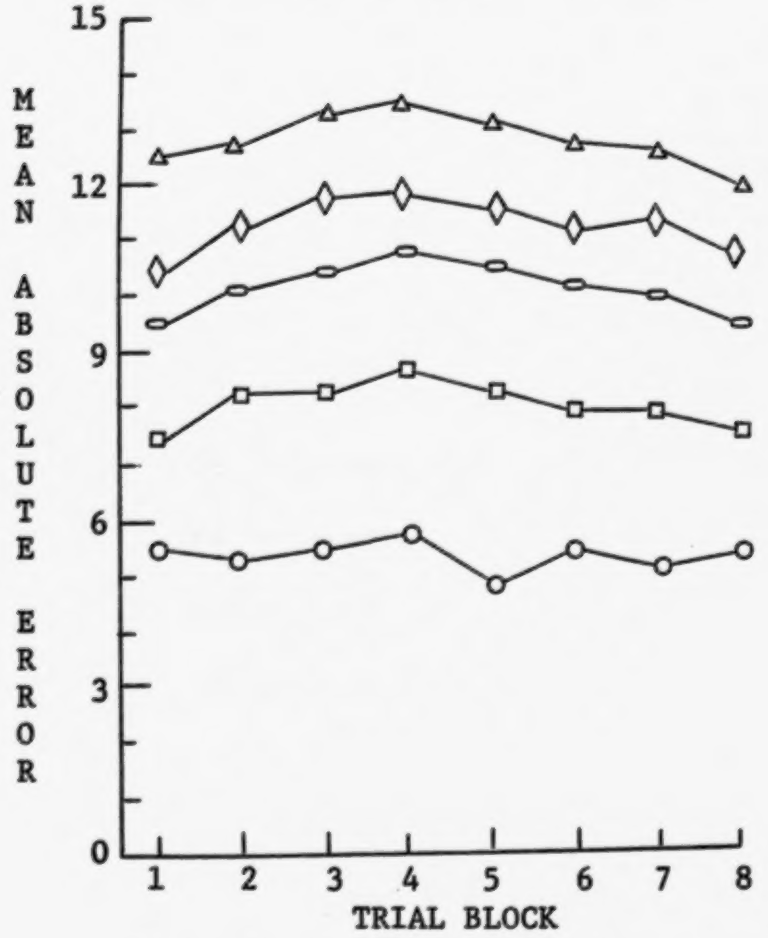


Fig. 78. Comparison of the error of prediction of the five integration formulas (P1, P2, P3, P4 & P5). Retarded Group. G3 formula.

○——○ P1

□——□ P2

⊖——⊖ P3

◇——◇ P4

△——△ P5

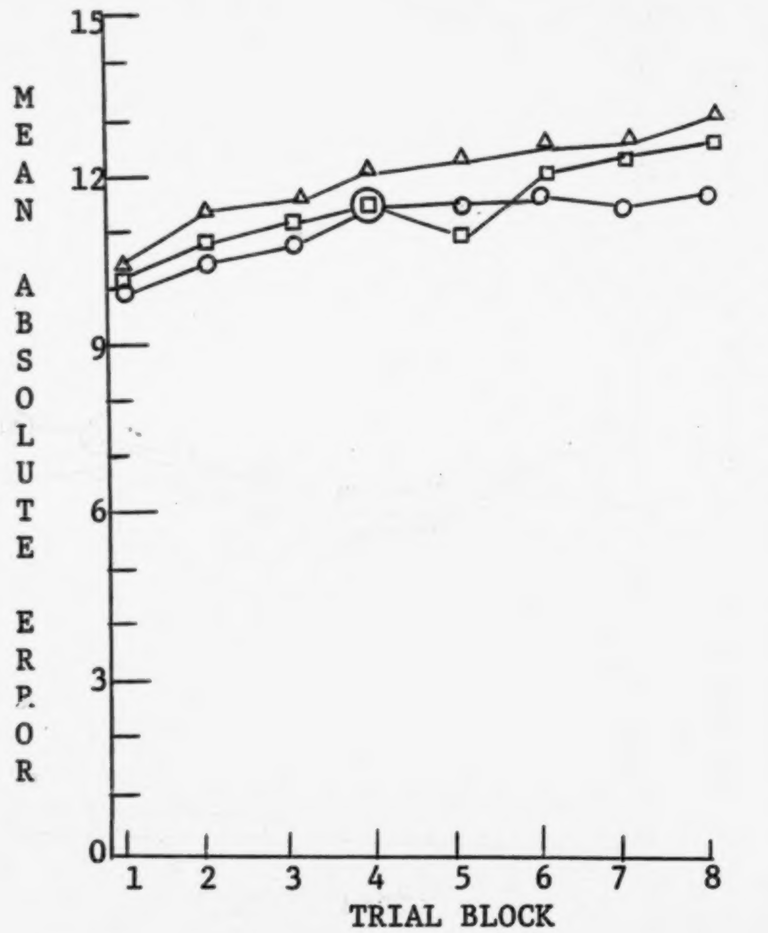


Fig. 79. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). High School Group. P1 formula.

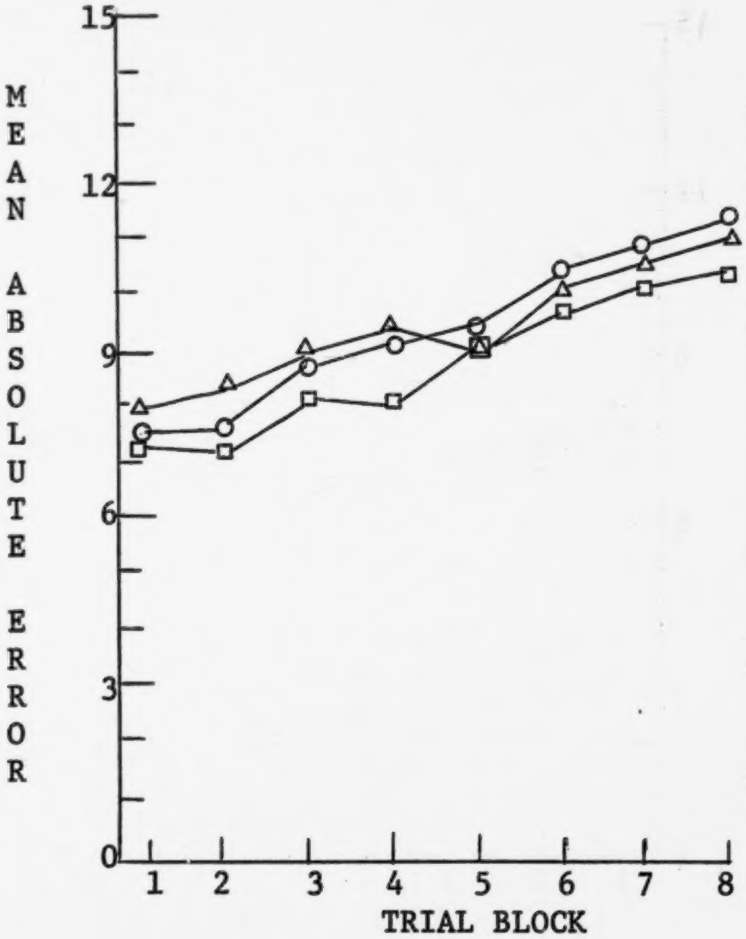


Fig. 80. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Grade School Group. P1 formula.

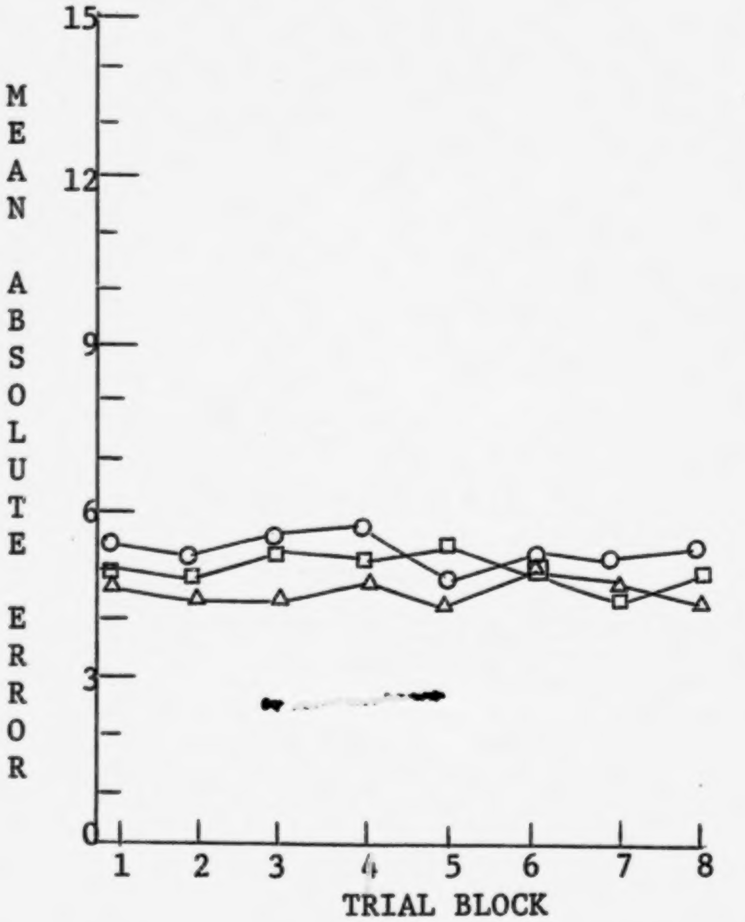
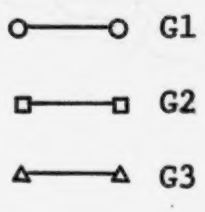


Fig. 81. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Retarded Group. P1 formula.



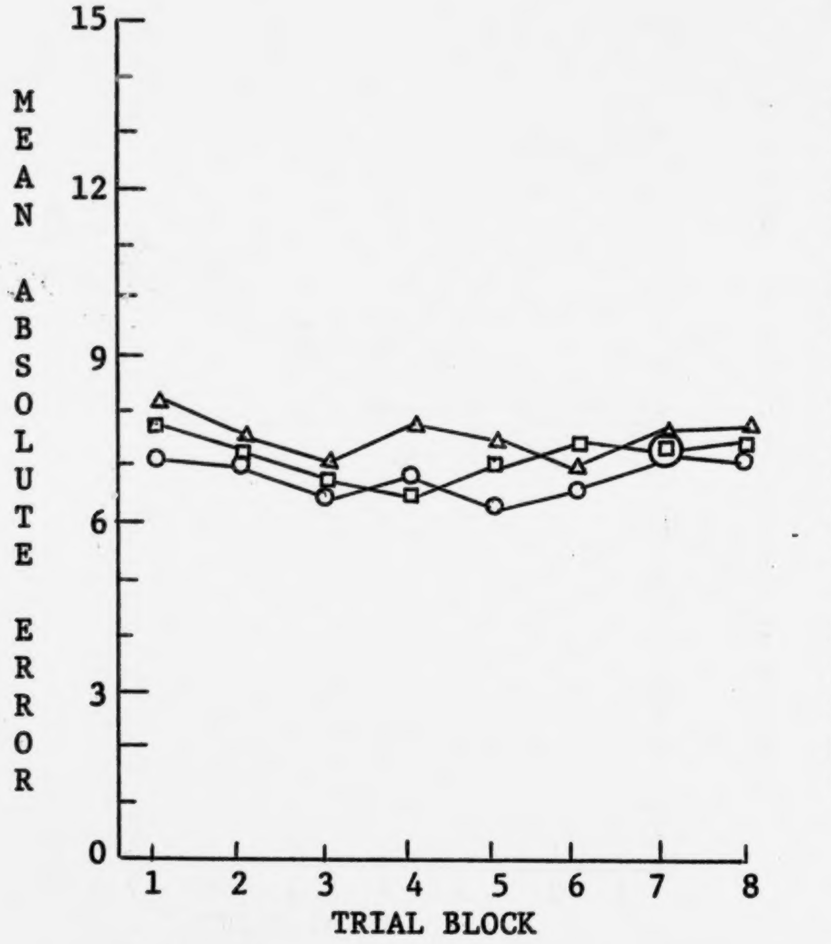


Fig. 82. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). High School Group. P2 formula.

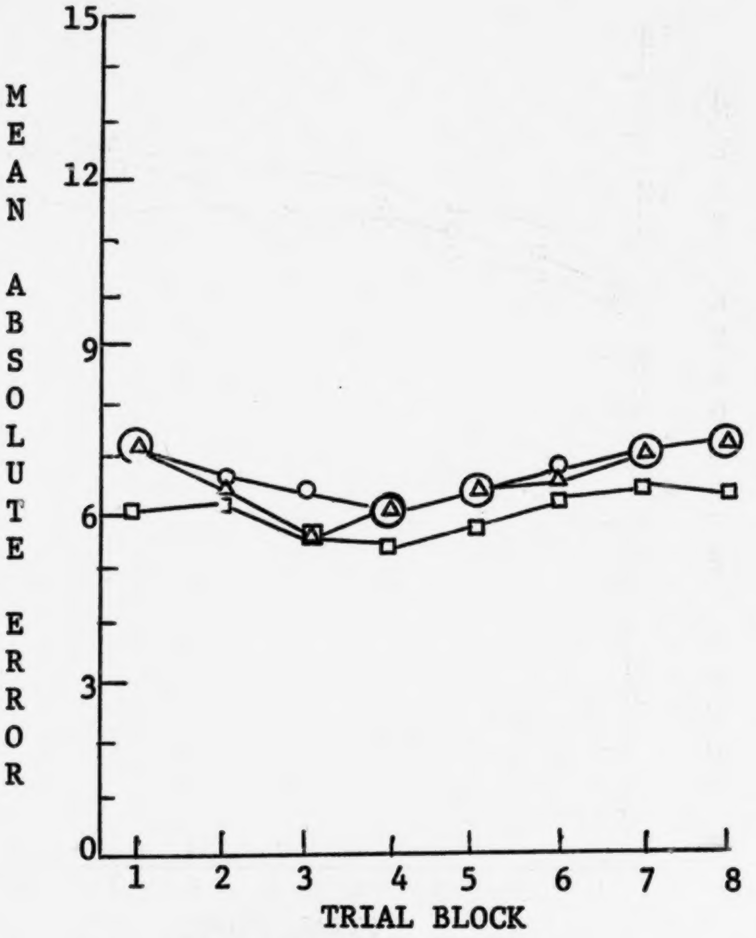


Fig. 83. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Grade School Group. P2 formula.

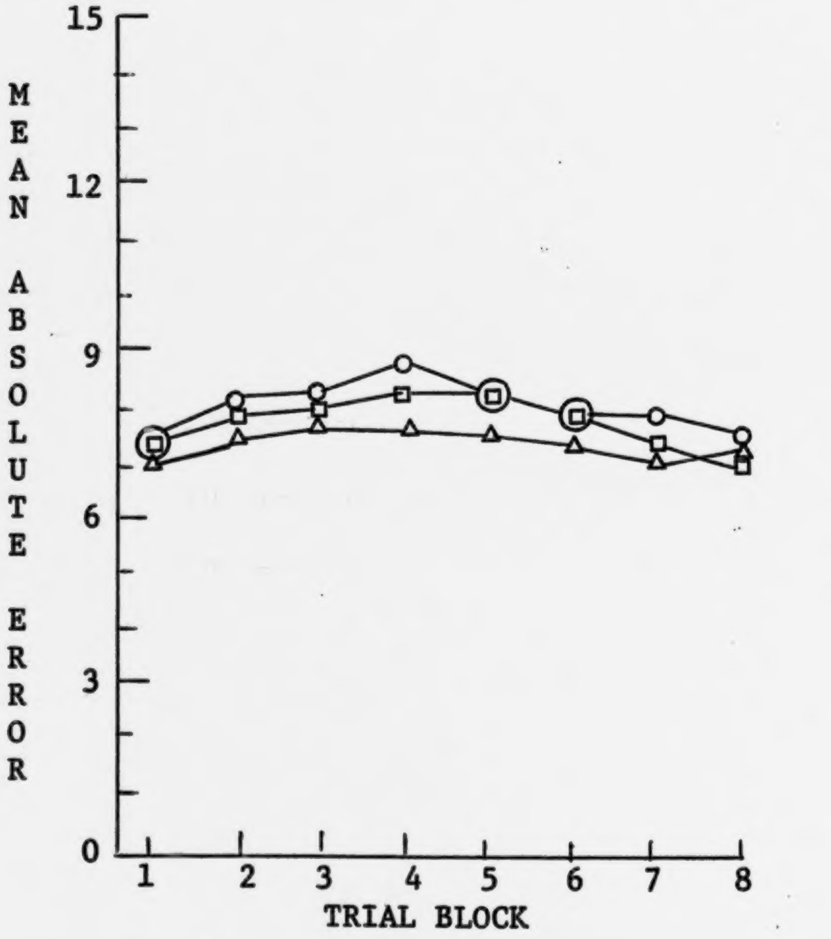
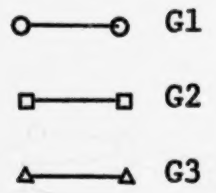


Fig. 84. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Retarded Group. P2 formula.



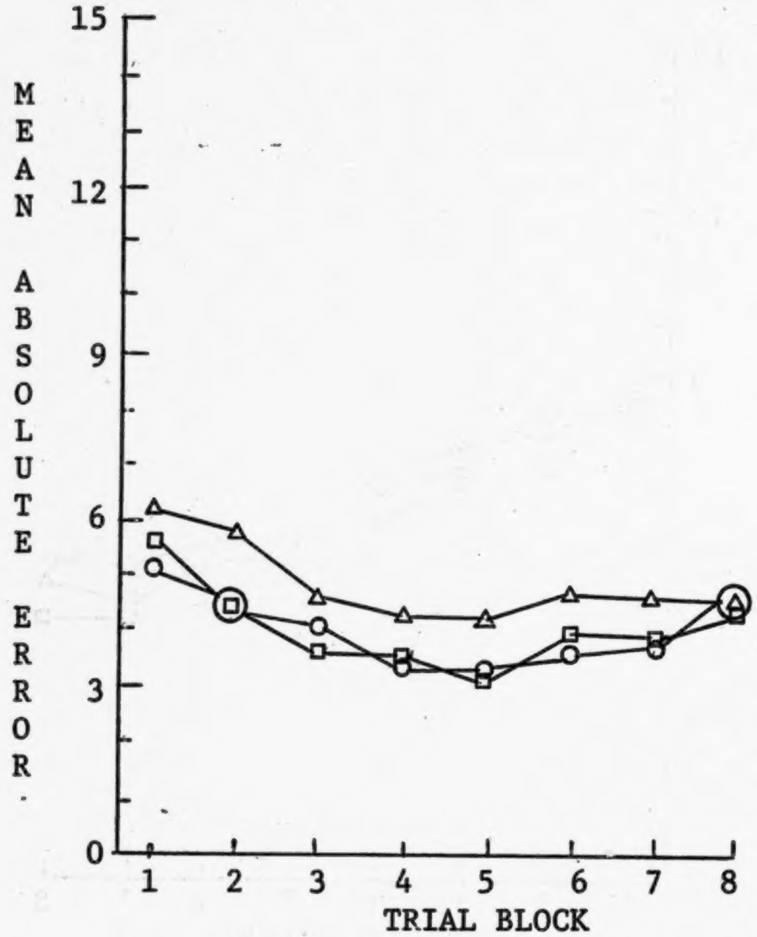


Fig. 85. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). High School Group. P3 formula.

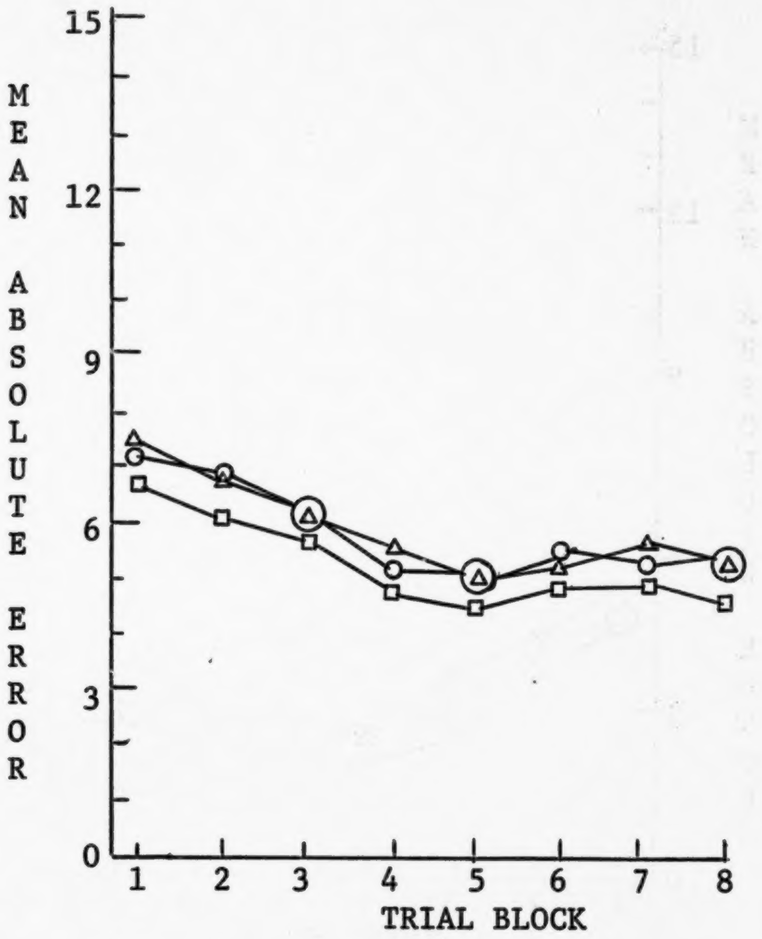


Fig. 86. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Grade School Group. P3 formula.

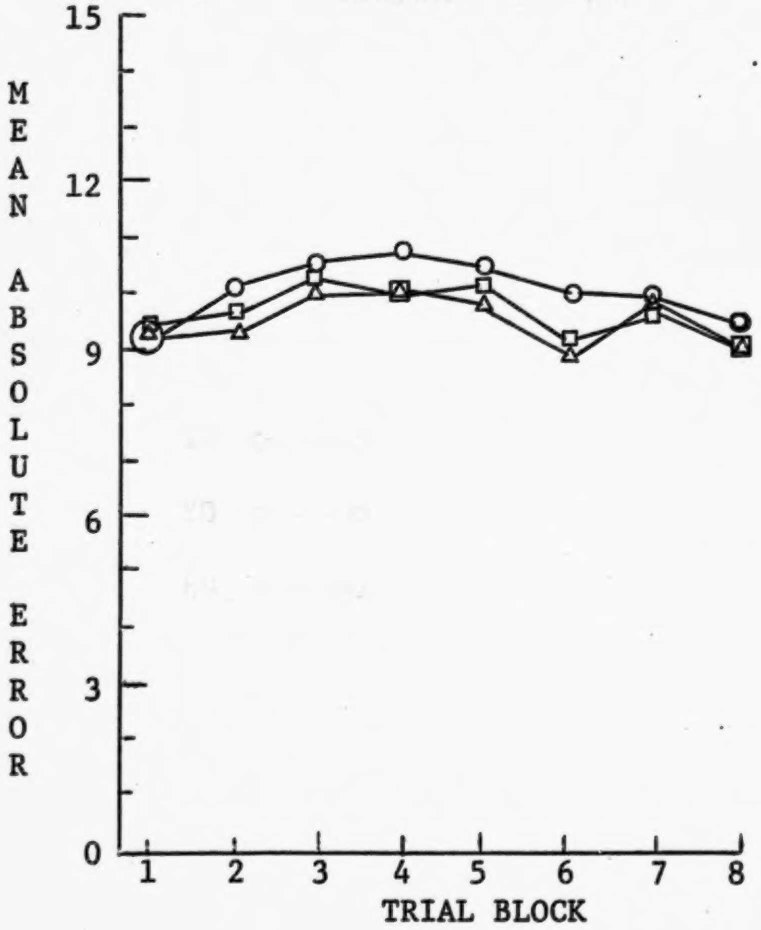


Fig. 87. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Retarded Group. P3 formula.

○——○ G1

□——□ G2

△——△ G3

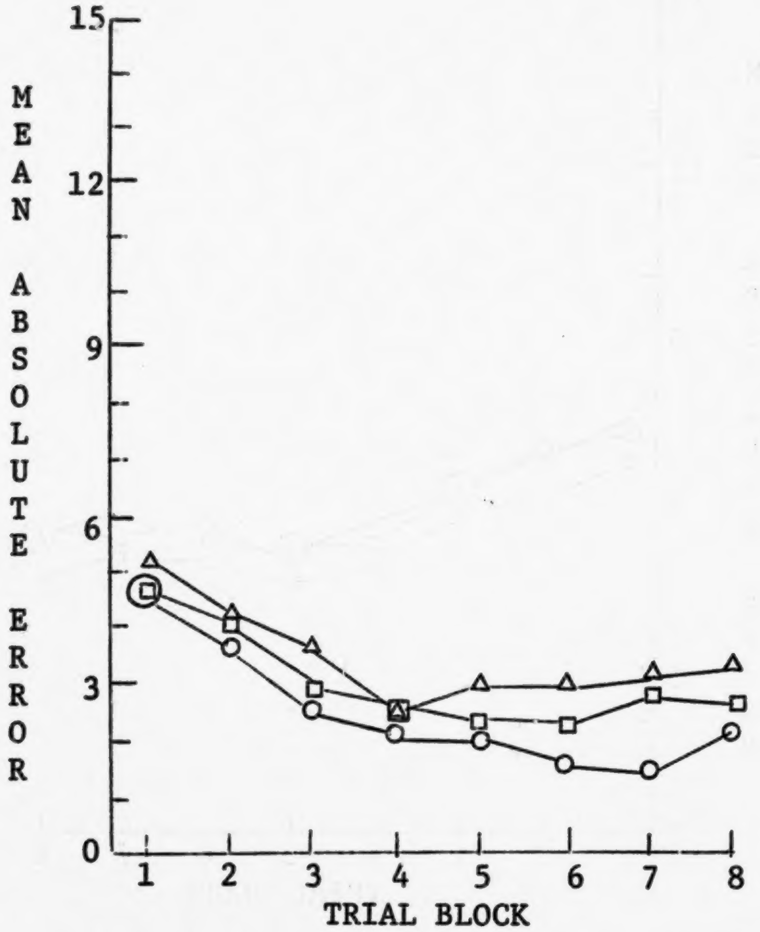


Fig. 88. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). High School Group. P4 formula.

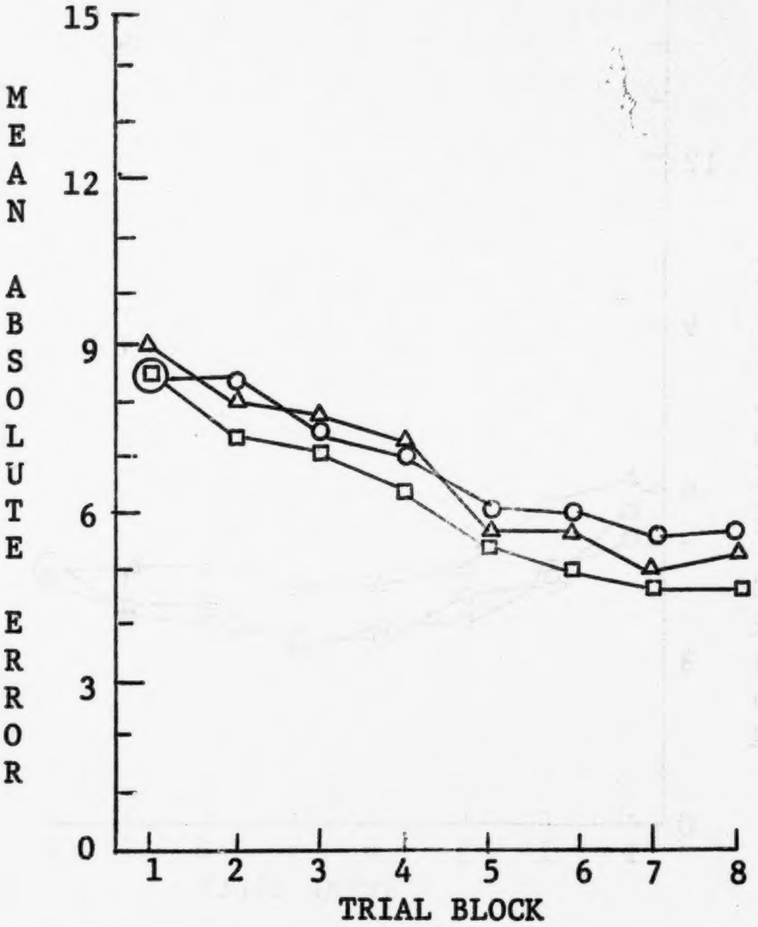


Fig. 89. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Grade School Group. P4 formula.

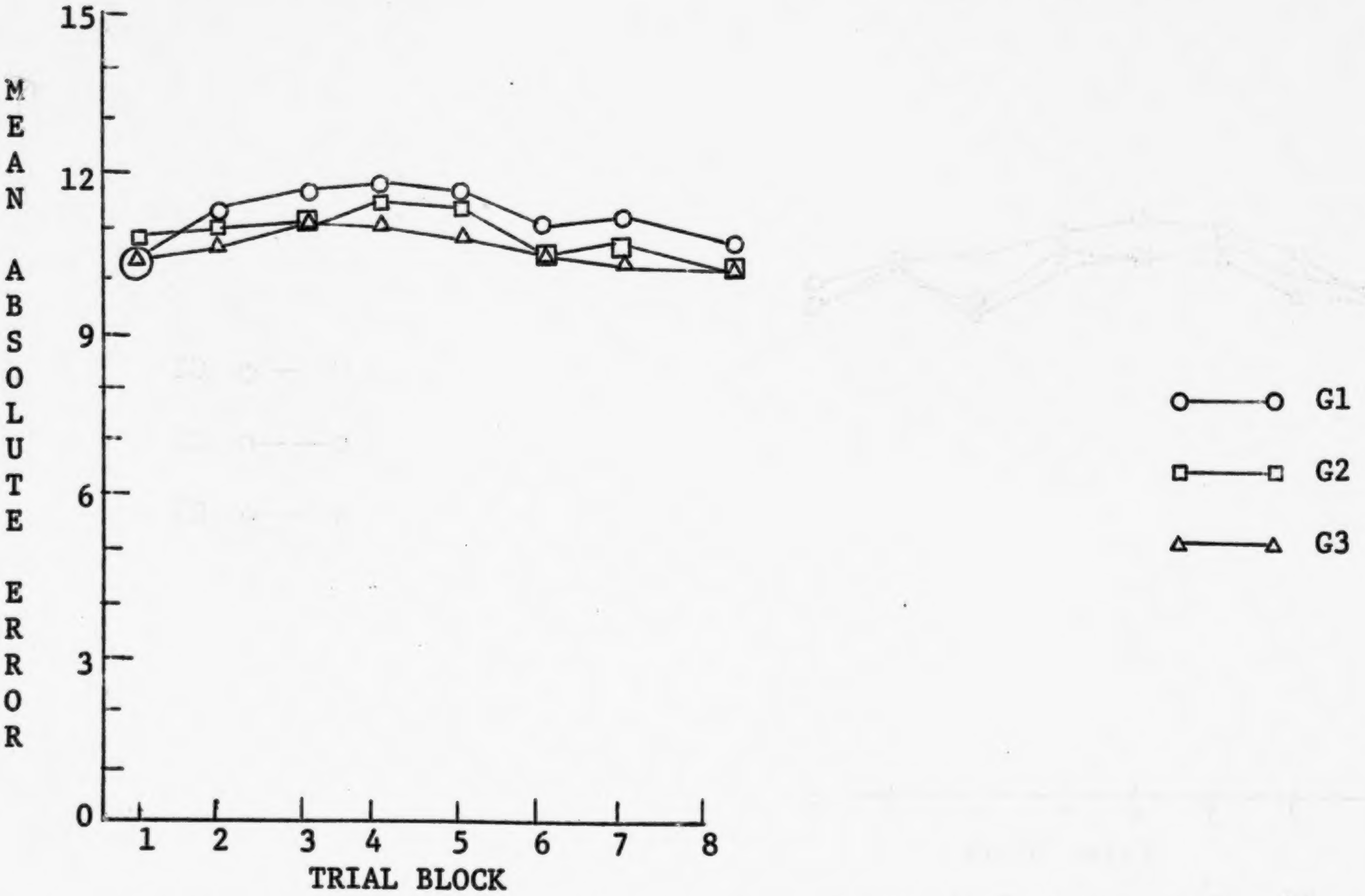


Fig. 90. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Retarded Group. P4 formula.

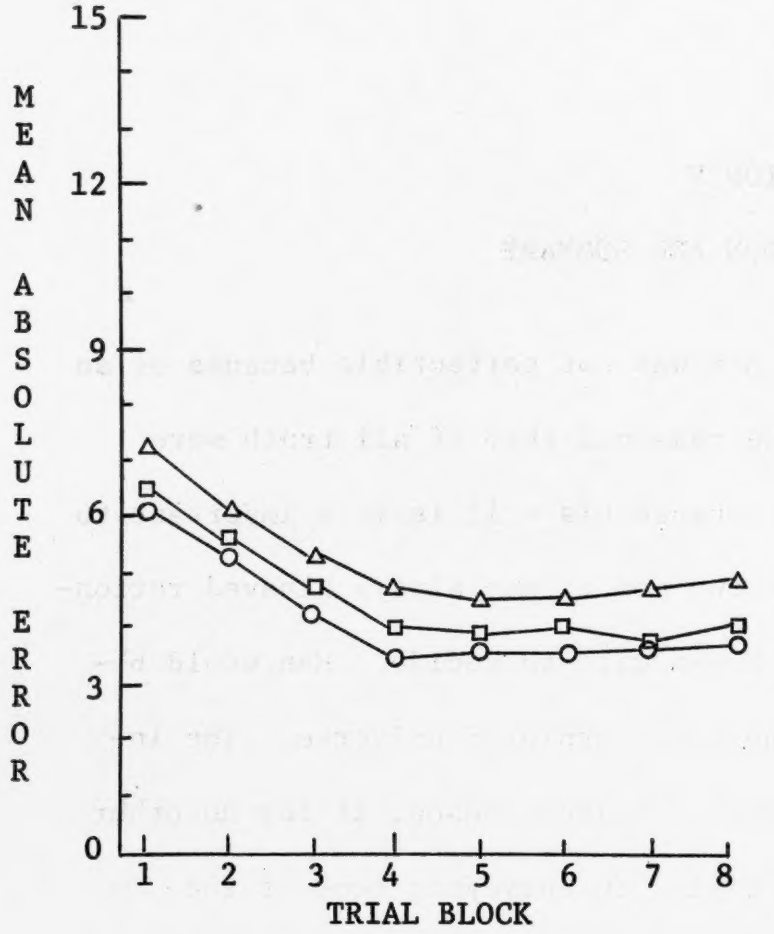


Fig. 91. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). High School Group. P5 formula.

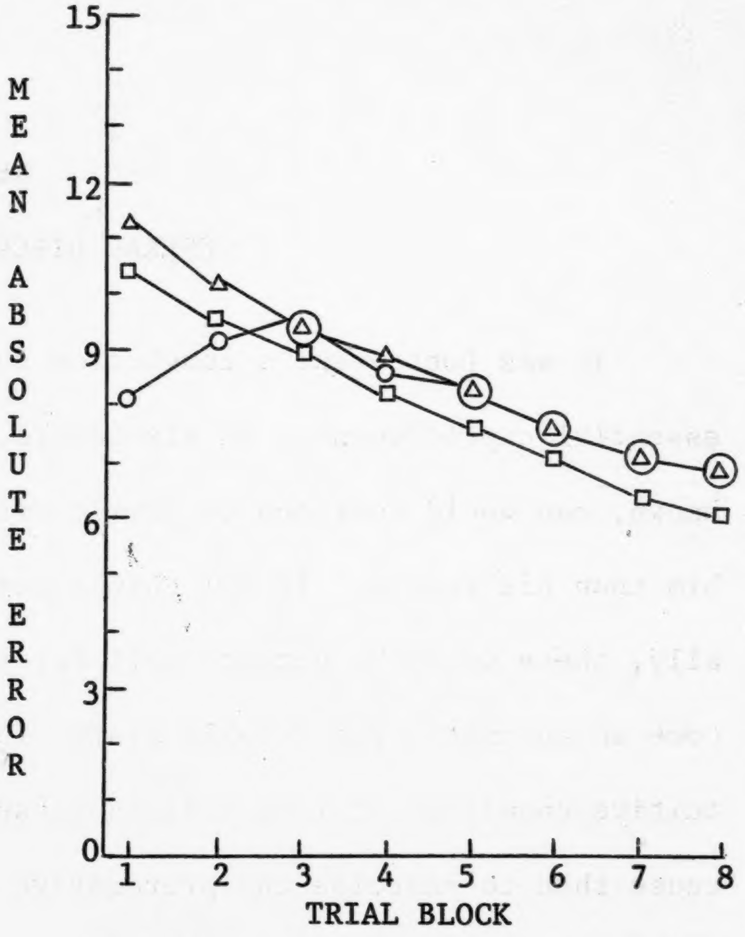


Fig. 92. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Grade School Group. P5 formula.

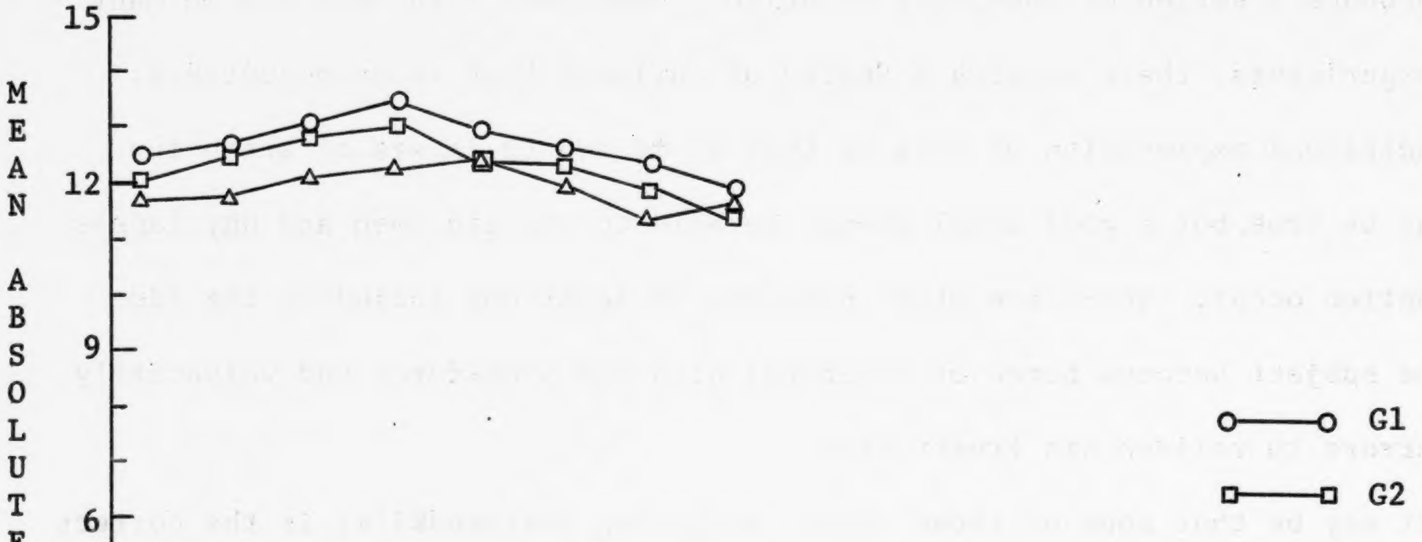


Fig. 93. Comparison of the error of prediction of the three generalization formulas (G1, G2 & G3). Retarded Group. P5 formula.

SECTION V

GENERAL DISCUSSION AND SUMMARY

It was Dostoevski's conviction that man was not perfectible because of an essential capriciousness in his nature. He reasoned that if all truth were known, man would continue to commit error because his will is more important to him than his reason. If all things were known and if man always behaved rationally, there would be nothing left for the human will to decide. Man would become an automatic predictable system in the fully explored universe. The intuitive knowledge of this dilemma causes him to reject reason, if for no other cause than to exercise the prerogative of will. In surveying some of the individual performances in this study one would almost tend to agree with Dostoevski. After gaining a very high plateau of reinforcement a subject will sometimes produce a series of seemingly irrational responses. In this, as in many other experiments, there remains a degree of variance that is unaccountable. One traditional explanation of this is that it is due to lapses of attention. This may be true, but a good model should be able to explain when and why lapses of attention occur. There are other possible explanations including the idea that the subject becomes bored or resentful with the procedures and voluntarily makes errors to relieve his frustration.

It may be that none of these ideas, including Dostoevski's, is the correct one. If the scientific equivalent to hedonism (reinforcement theory) is correct, it is difficult to see why it should be periodically cancelled or if not cancelled, why the needs of the organism should oscillate in so arbitrary a manner.

It is difficult to believe that man could have made his evolutionary journey if will really predominated over reason. There may exist in man a kind of rationality that transcends the rationality of laboratory learning and perception.

He may be endowed with a mechanism that periodically causes him to take "long shots." Consider the relative ability of two species to survive, one of which always behaves on the basis of previously reinforced responses and the other which deviates from this in some, as yet unaccounted for, manner.

If, in the history of both species, it was found that response R_1 led to reinforcing consequences and R_2 led to negative effects, in a short time one of the species would quit sampling R_2 altogether. The other species would continue to do so from time to time. Now let it be supposed that the environmental situation changed abruptly such that R_2 began to yield desirable or useful consequences. The species showing some degree of behavioral heterogeneity would pick up some definite advantage in the competitive struggle since the other group would not deviate from its stereotypic solution to the situation. Thus man's apparent capriciousness can be thought of as a continuous effort to retest reality. It is not clear at this time how such an idea could be incorporated into a model of individual behavior. There may be, however, some physical correlate to the occurrence that could be sensed; or even some, as yet unapprehended, sequential pattern of responding that is to some extent peculiar to each individual, which would serve as index that the response was about to occur.

Although it is quite likely that better models of group behavior can be obtained than the one presented here, it seems likely that future programs will be more beneficial if they make a critical examination of individual rather than group behavior. The behavior of the group is, after all, a kind of mathematical abstraction which is useful in the evaluation of a critical hypothesis but has limited descriptive value. If, due to our lack of understanding, individual behavior is still too variable to be comprehended within a model, consideration should be given to statistics other than means, standard deviations and the like.

Perhaps what is needed is a kind of multivariate analysis using modes or medians rather than means. In any case, we should remember that the success of our models relates as much to our mathematics as it does to any definite idea we may have about the nature of the organism.

This research seems to have established three things. First, and perhaps most important, is that it has shown that perceptual behavior, whether that of normal or retarded subjects, can be very closely approximated by a single basic model. The variation between best solutions is seen to be a quantitative rather than a qualitative difference. One cannot say, of course, that in the future other models which differ quantitatively will not be developed which are more precise than the model evaluated here. For the moment, however, the results are encouraging since they suggest that rather than finding the mentally retarded to consist of a number of intrinsically separate or discontinuous populations with respect to perceptual learning, continuity does exist between them and indeed between them and the normals.

The second observation that can be made from these data relate to stimulus generalization. It is not surprising, of course, that in the case of the retarded the effect of reinforcement on one stimulus irradiates to adjacent stimuli in a less discriminating manner than it does with normals. The value of the work is that stimulus generalization has been quantified at least in a relative sense for the two populations. Intelligence to some extent can be related to the slope of the generalization curve.

Finally, we see that intelligence is also very much a function of the emphasis that is placed upon high and low probability events as compared to events of medium probability. To a much greater degree than the retarded, normals base their decision on the more distinctive properties of the stimulus configuration.

Medium probability events exercise an influence but a disproportionally low one. In general it can be said that this tendency is mathematically valid, but the evidence is that the normals go even beyond what can be mathematically justified in their perceptual decisions. This is not to argue that their behavior is irrational. To pick up an earlier argument, there may be a rationality here that transcends the ordinary ideas of probability.

Although this research was descriptive and did not have as a central objective an exploration into the diagnostic or pedagogical aspects of mental retardation, it is, notwithstanding, appropriate to consider what the present finding may have to contribute to these areas. It can be said that it would be fairly simple to produce a diagnostic instrument on the basis of these studies. There is, moreover, reason to assume that such an instrument would be fairly precise, although how well it would compare with the tests of intelligence in current usage cannot, at present, be judged. It would have certain advantages over such tests as the WISC and Stanford Benet, however, because it would not be linguistically or ethnically limited. Presumably it would relate more nearly to innate intellectual capacity than do these other tests, since they are much influenced by the degree of richness of the cultural environment to which the individual has been exposed. The unique feature of such a test, however, is that it would be based not on performance, as are other intelligence tests, but rather by a measurement of the process out of which performance occurs.

It is the intention of the experimenter to explore further into special application of the findings, especially in the area of diagnosis. There exist many possibilities for future research in continuation of this work. It would be of interest, for example, to learn if the synthesis of emotional patterns obey the same general rules as were found here for sensory patterns. If evidence of emotional dislocations were found using this analytical technique, the test might prove of value to the problems of psychiatry.

All of this, however, is at present hypothetical. It is submitted, nevertheless, that the general approach of quantifying human perceptual habits in order to apply the findings to problems of training, diagnosis and therapy has much promise for the future.

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ABSTRACT

Two experiments were conducted in order to obtain a mathematical description of the perceptual process by which normal and mentally retarded subjects synthesize stimulus cues in perceptual identification. The initial study employed college students, grade school students and mentally retarded children as subjects. The subjects were required to make a binary classification of four hundred pictures in which three stimulus cues were shown through twenty variations. The variations were related to the classifications in a probabilistic manner. In the second study, high school, grade school and retarded subjects were required to make a similar classification of four hundred pictures in which four stimulus cues were present. Subjects were required to place a wager on whether a picture belonged to one or other of the two classifications. Subjects were allowed to vary the amount wagered. It was assumed that the amount was a quantitative index of the subject's degree of certainty of the classification. It was established that as mental age increases there is a greater tendency for high and low probability events to influence the evolution of a percept. Also noted was a more promiscuous irradiation of the effect of reinforcement (stimulus generalizations) for subjects of low intelligence. A model was contrived in description of the data, and suggestions were made for an application of the findings to the education and diagnosis of the mentally retarded.